Masters thesis: Automated ECG Analysis using Weightless Neural Networks

Wouter A.Th. Manintveld

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Automated ECG Analysis using Weightless Neural Networks

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Wouter A.Th. Manintveld

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TU Delft

Department of Applied Mathematics
and Computer Science
Delft University of Technology
The Netherlands
&
Department of Electrical and Electronic Engineering
Imperial College of Science, Technology and Medicine
London, United Kingdom

Foreword

This is the final report of the project I did from October 1995 till June 1996. This project concludes my study of Computer Science at Delft University of Technology. The project was performed at the Neural Systems Group at Imperial College of Science Technology and Medicine, under supervision of Prof. Igor Aleksander (Imperial College), Prof. Henk Koppelaar (Delft University of Technology) and Dr.Drs. Leon Rothkrantz (Delft University of Technology). This thesis is submitted in partial fulfilment of the requirements of the degree of Engineer (*Ir.*) of Delft University of Technology, and the International Diploma Imperial College (*IDIC*).
At Delft University of Technology my examiners are (ordered alphabetically):

Prof. I. Aleksander (IC London)
Prof. E.J.H. Kerckhoffs (TU Delft)
Prof. H. Koppelaar (TU Delft)
Dr.Drs. L.J.M. Rothkrantz (TU Delft)

At Imperial College my examiners are:

Dr. P. Cashman (IC London)
Dr. S.J. Roberts (IC London)

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Abstract

A Weightless Neural Network has been used for the classification of electrocardiograms (ECG's). The algorithm was tested on the standard MIT-BIH database. Weightless Neural Networks are based on the n-tuple classification method and are very powerful tools for pattern recognition tasks owing to their speed, for both training and testing, and their training capabilities.

The method used consists of two stages: preprocessing of the data, and a neural network based classification stage. For each class of beats a weightless discriminator is trained, and during generalisation the discriminator with the highest output determines the class of the input pattern.

The system was tested and analysed. The weightless neural approach enables testing of a lot of different parameters setups, due to its lightning speed.

The results of a one-lead ECG classification system, based on this rather brute force approach, were encouraging. With a correct classification of approximately 97 percent, this system can be a suitable basis for an ECG-diagnosis system.

Chapter 1

Problem Description

Heart disease is the most common cause of death in the western world. Patients with heart related diseases need considerable attention from hospital personnel because of the constant danger of complete heart failure. Electrocardiography is an effective non-invasive diagnostic technique, which is widely used by cardiologists. Electrocardiograms (ECG) are electrical views of the heart, recorded by placing electrodes on the patient's body. ECGs provide the cardiologist with useful information about the rhythm and functioning of the heart. Beats extracted from ECG signals can be categorised in a range of classes, i.e. normal, atrial premature or ventricular escape beats.

In recent years considerable research has been done to assist cardiologists with their task of diagnosing the ECG recordings. The research fields range from novelty detectors to fully automated ECG diagnosing systems. A wide range of techniques have been used, including statistical pattern recognition, Expert Systems and Artificial Neural Networks.

The Artificial Neural Network techniques are used for a variety of tasks, but most of the tasks are related to detection of irregular beats, and the kind of irregularity, in the recordings. Most of the conventional neural techniques, like backpropagation and Radial Basis Functions have been tested, some with very promising results.

A very powerful, but somewhat unorthodox, neural technique is the Weightless Neural Network. It is a very useful technique for pattern recognition, for example in images. Weightless Neural Networks are called 'unorthodox' because of the omission of weights. Instead a look-up table approach is used.

In this project the use of Weightless Neural Networks in ECG analysis will be researched. The goal is to classify beats extracted from ECG signals into predefined classes, using weightless techniques. This classification is very useful: it can save cardiologists a considerable amount of time. For example, if an automated ECG analysing system can provide the cardiologist with the 'interesting' beats in a long recording, the cardiologist can make his diagnosis on these beats.

The system will be based on the WISARD architecture, a weightless multi-discriminator setup. The morphology of the data will be used as input for the system. No feature extraction will be necessary.

This research is not only to investigate the usefulness of weightless neural networks in ECG Analysis, but is also to make a comparison of weightless systems with other neural techniques.

Chapter 2

The Heart

The centre of the cardio-vascular system of the human body is the heart. This chapter describes how the heart works, what can go wrong with it and how it can be monitored. It should provide the reader with the necessary knowledge to understand the medical side of this thesis.

2.1 Anatomy

The heart can be considered as a four chambered, muscular pump. It receives oxygen deficient blood from the body, sends it to the lungs to get a fresh supply of oxygen, and pumps this oxygen rich blood back round the body. In normal conditions it beats at an average rate of 70 beats per minute.

The anatomical structure of the heart is shown in figure **??**. The left side of the heart is the larger and thicker side. It does more work because it pumps oxygenated blood into the aorta (the main artery of the body) and then throughout the entire body. The thinner, right side of the heart pumps the same amount of blood, but only has to send it a short distance into the lungs via the pulmonary arteries.

Each side of the heart consists of two chambers, an atrium and a ventricle. The thick-walled ventricles are the larger pumping chambers that expel blood from the heart with each beat (*contraction* or *systole*). The relative thin-walled atria function as collecting and loading chambers. The atria hold blood being returned to the heart during ventricular systole. In between beats, the ventricles are relaxed (*diastole*). During diastole , blood flows into the ventricles from the atria — at first passively, and then propelled by atrial contraction (*atrial systole*).

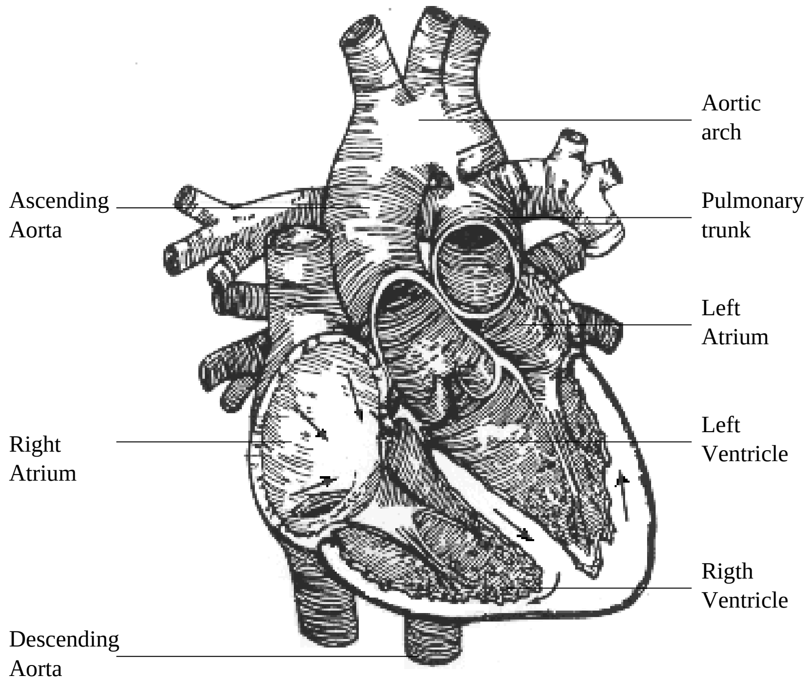

Figure 2.1: The human heart

Strategically located valves prevent back-flow of the blood: the mitral valve between the left atrium and ventricle; the aortic valve between the aorta and left ventricle; the tricuspid valve between the right ventricle, and the left atrium and the pulmonary valve between the main pulmonary artery and the right ventricle.

Due to inter-collated discs the cells of the heart muscle act together in order to contract synchronously. The contraction is initiated by a built-in pacemaker that is independent of the central nervous system. A special nervous tissue in the right atrium is called the *sino atrial node*; it is responsible for initiating contraction. The signals are passed down various pathways to the atria-ventricular node. This causes the two atria to contract. The nervous signal then travels down the atria-ventricular bundles to initiate the contraction of the ventricles.

The heart muscle is of a special type, called cardiac. Figure **??** is a diagram of a cross section through the heart. The *endocardium* is a layer of smooth lining cells. These cells are found not only in the heart, but also on the inside of all the blood vessels of the body, where they are called *endothelium*. The *myocardium* is the mass of the heart muscle cells whose coordinated contraction causes the chambers of the heart to contract and pump blood. The myocardium is thin in the atria,

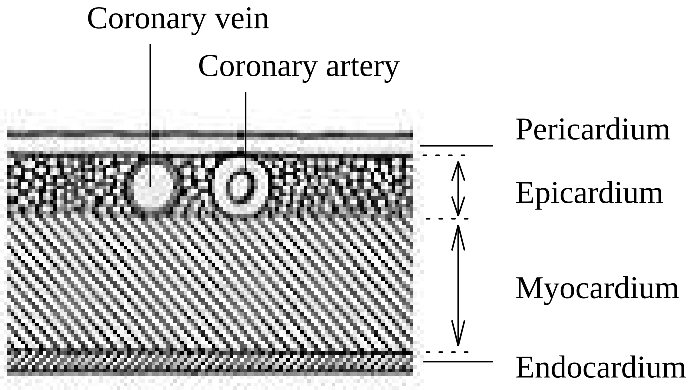

Figure 2.2: layers of the heart muscle

thicker in the right ventricle and thickest in the left ventricle. The *epicardium* is a fatty layer on the outer surface on the myocardium. The major *coronary blood vessels*, the vessels that supply blood to the heart itself, run through the epicardium. The outermost layer is the *pericardium*, actually two layers with a small amount of lubricating fluid between them, forming the *pericardial sac* which encloses the entire heart.

2.2 Inspection of the Heart

There are several ways to inspect the size, shape and functions of the heart:

- Touching the chest. If the tip of the heart can be felt pushing against the chest, the heart may be enlarged. Knocking lightly on the chest gives an idea of the heart's shape.

- Listen with a stethoscope on the chest to hear the sound of the heart. The normal heart sounds, lub and dub, can be heard. Any unusual sounds can also be heard. Heart arrhythmias and murmurs are two possibilities. An arrhythmia is an irregular pattern of the heart's beat. A murmur indicates that blood is seeping through the closed valve separating the atrium and ventricle.

- Making an x-ray. This 'shadow' picture of the heart shows the size and position of the heart, and can also show any obvious deformities.

- Echocardiography. Pulses of high-frequency sound are transmitted into the body and the resulting echoes are recorded and can be visualised. A common use of this technology is to picture the foetus inside the mother's womb. Another use is to picture the heart's size, shape and movement.

- ElectroCardioGraphy (ECG). The electronic activity of the heart muscle can be viewed by placing electrodes on the patients body. See section **??**.

- Invasive Procedures. Surgery on the heart is a last resort; in most cases the ways to inspect the heart as described above are adequate.

2.3 ECG's

Electrocardiogram's(ECG's) are recorded by an *electrocardiograph*. This machine records electrical currents picked up by special wires (*electrodes*) attached to particular parts of the body. ECG used to be paper strips on which the detected wave form was written (see figure **??**). Nowadays most of the ECG are recorded digitally, or on magnetic data tapes.

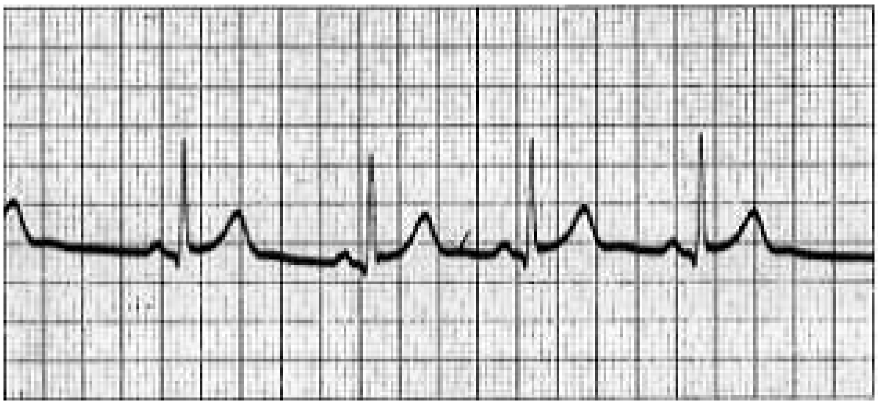

Figure 2.3: An ECG strip

The current recorded by the electrocardiograph at any moment is the sum of all the currents flowing in cells throughout the heart at that particular moment, and is measured in millivolt. The zero millivolt line is called the *baseline*, and movements of the signal from this line are called deflections.

Resting cardiac muscle cells (myocardial cells) maintain a small electrical charge across their cell membranes. Loss of this electrical charge(*depolarisation*) occurs with a short, outward flow of current and initiates contraction of the muscle cells. After a short interval, the cells regain their charge (*repolarisation*) with a short inward flow of the current and are ready to contract again.

When current flows toward the recording electrode, the deflection is positive (upward), so that an upright wave will be recorded. Conversely, current flowing away from the electrode results in a negative (downward) deflection.

The conventional electrocardiogram consists of 12 leads, that is, 12 different electrical views of the heart. The first six leads are the frontal plane leads, and are called I, II, III, V_R, V_L, V_F[1]. Lead V_R, V_L and V_F are called *augmented limb leads*; this because they are recorded by electrodes on respectively the *R*ight arm, the *L*eft arm and the le*F*t leg. The right leg electrode is connected to the ground. Leads I, II and III are called standard leads and represent subtraction of the electrical potentials recorded by the limb leads:

$$\begin{aligned} \mathrm{I} &= V_L - V_R, \\ \mathrm{II} &= V_F - V_R, \\ \mathrm{III} &= V_F - V_L. \end{aligned}$$

The other six are the *precordial* (in front of the heart) leads (V_1 - V_6). These are recorded by an array of six electrodes placed on the chest. Each precordial lead records the myocardial electrical currents as seen from its point of view, and is most sensitive to changes in the myocardium nearest it. Therefore leads V_1 and V_2 are most sensitive to events in the right side of the heart, and lead V_5 and V_6 to the left side. The mean axis is the average direction of atrial and ventricular depolarisation.

Some leads of normal ECG-beat resemble the drawing in figure **??**, but there will be some disturbances because of the 'noise' produced by muscles other than the heart.

2.4 The Waves

Normal movements from the baseline are called waves, and are designated P, QRS, and T. The space between the waves, which usually appear as straight lines, are

[1] for convenience also called R, L, F

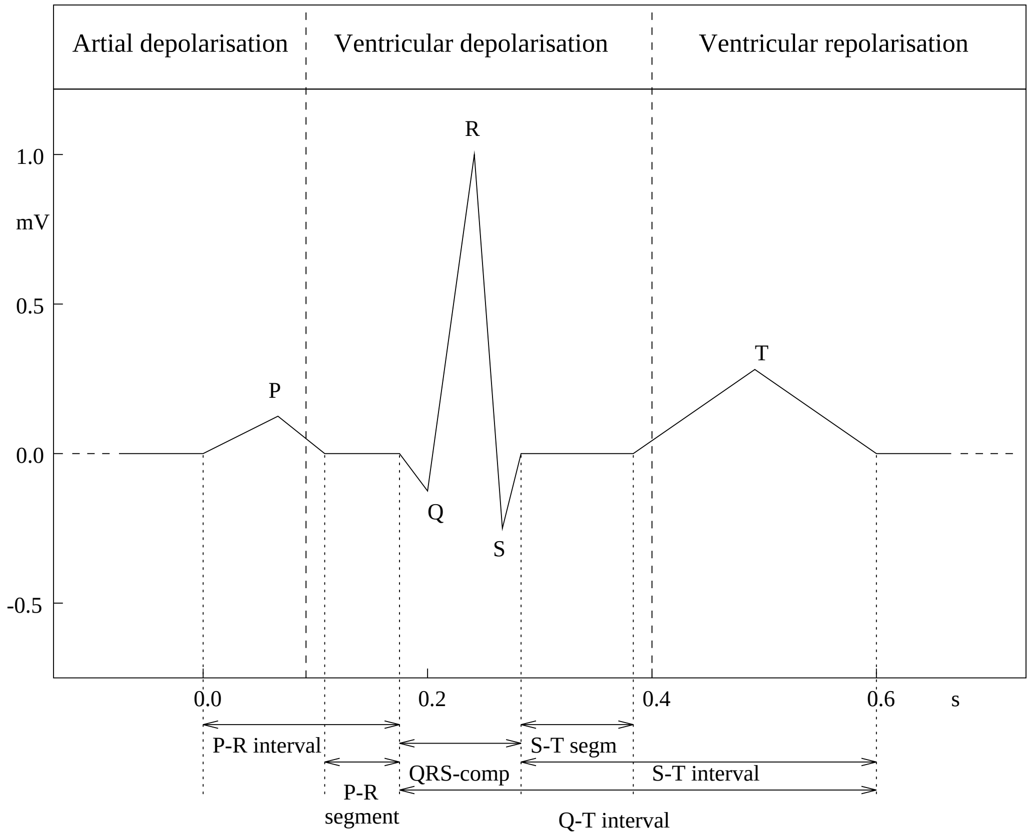

Figure 2.4: an ECG beat

called *segments*, and are named by the waves they separate. *Intervals* are also named by the wave at their beginning and end, but their measurement is from the beginning of the first wave.

The first deflection of the cardiac cycle, the *P wave*, is caused by depolarisation of the atria. The P wave is a small, rounded wave. The *PR segment* (strictly speaking the PQ segment, but conventionally referred to as the PR segment) separates the P wave from a large sharp deflection, the *QRS complex*, which is caused by the depolarisation of the ventricles. An atrial repolarisation wave (*atrial T wave* or T_p *wave*) directed opposite to the P wave is seen occasionally, but is usually obscured by the QRS complex.

The QRS complex may consist of one sharp up and down wave, but more often it has several components, which are defined as follows: The *R wave* is the first upward deflection; the *Q wave* is a downward deflection that precedes an R wave; the first downward deflection after the R wave is an *S wave*; if the entire complex is negative, it is called *QS*. There may be a second R wave — if so, it is designated R′ (R prime); the second S wave is called S′; rarely, R″ and S″ are also present. To be separately labelled as part of the QRS, the wave must cross the *baseline*. Every wave changes direction once, but a second change which does not cross the baseline is called a notch.

An abrupt change in the direction of the wave marks the end of the QRS complex and the beginning of the ST segment. This point is called the J junction, or the *J point*. The ST segment may be above ("elevated"), at or below ("depressed") the level of the baseline. The ST segment is followed by a large, rounded *T wave*, which corresponds to ventricular repolarisation. The T wave may be notched, inverted of biphasic. Sometimes another rounded wave, the *U wave*, follow the T wave. The source of this U wave is uncertain. It is sometimes recorded from normal hearts, but when large it is often a sign of drug effect or electrolyte imbalance.

Not all the leads mentioned in section **??** show all the waves mentioned in figure **??**. The placement of the electrodes can make the recording of some events in the heart undetectable.

2.5 Important Features

Important measurements that can be taken from a ECG signal include [**?**]:

Rhythm Under normal conditions a heart beats between 60 and 100 times per minute, and the atria and the ventricles beat at the same rate. See table **??**.

category	*bpm*
adult Males	about 72
adult Females	76 to 80
newborns	up to 140
children	about 90
elderly	50 to 65

Table 2.1: Average Pulse Rate

Wave height All R waves, or peaks, should be of approximately the same height. Under normal condition this is about 0.9 mV. When a disease causes a heart chamber to enlarge, one of the best signs is an increase in the height of the wave generated by that chamber.

PR interval The PR interval extends from the beginning of the P wave to the beginning of the QRS complex. A normal PR interval may be as short as 0.12 seconds or as long as 0.20 seconds.

QRS duration The QRS duration is measured from the beginning to the end of the QRS complex; it is the time required for the ventricles to become completely depolarised, and should not exceed 0.10 seconds.

QT interval The QT interval extends from the beginning of the QRS complex to the end of the T wave. Its length varies with the heart rate. For a normal rate it should be less than 0.40 seconds. When it is longer the heart is at greater risk of developing serious and potentially fatal arrhythmias.

QRS axis The mean frontal QRS axis is a measurement of the direction of the average QRS force in the frontal plane (constructed of the first six electrocardiographic leads I, II, III, R, L, F). It is important to know whether the axis is normal or abnormally shifted to the left or the right, to evaluate conduction within the heart.

ST segment This segment can be depressed or elevated relative to the baseline. This can be caused by *myocardial ischemia*, a reduction of blood flow to part of the heart (but not enough to cause an acute infarction). This can be accompanied by dangerous ventricular arrhythmias or heart block.

2.6 Disorders

This section describes the most important disorders that can be seen in electrocardiograms. The causes of these disorders are a subject beyond the scope of this project. This section focuses on how the disorders are manifested in the ECGs. Appendix **??** gives a more detailed description of the disorders, here they will be described briefly.

ECG event	*duration (seconds)*
P wave	0.06-0.11
PR segment	0.06-0.10
PR interval	0.12-0.21
QRS complex	0.03-0.10
ST segment	0.10-0.15
T wave	varies
ST interval	0.23-0.39
QT interval	0.26-0.49

Table 2.2: ECG events durations

2.6.1 Conduction Disorders

For the heart to pump blood effectively, the myocardial cells of each chamber must contract in a coordinated way. This coordination is achieved by impulses which originate in the *sino atrial node* (SA-node), the heart's own pacemaker. These impulses are conducted over specialised tissues to reach all parts of the heart at the proper time. The impulses are strong enough to stimulate first the atria and then the ventricles to contract, but too weak to be detected on the ordinary electrocardiogram. Nevertheless, malfunctions of any part of the conducting system can be readily diagnosed, since they cause delayed depolarisation of the atria, the ventricles, one ventricle or even part of a ventricle, resulting in characteristic changes in the electrocardiogrampattern.

Any abnormality of impulse conduction between the atria and the ventricles is called *atrioventricular block*. This includes abnormally slow conduction and the failure of some or all the atrial impulses to reach the ventricles. Atrioventricular blocks can be divided in three categories: First degree AV Block, Second degree AV Block (type I, type II and 2:1 block) and Third degree AV Block (complete heart block). Among ECG patterns related with AV blocks are Right Bundle Branch block and Left Bundle Branch Block.

2.6.2 Cardiac Rhythms

Under normal circumstances, the heart is under control of the sino atrial node, and each QRS complex is preceded by a P wave which is upright in leads I, II, V_F and V_6 (see page **??**). When the heart rate is between 60 and 100 beats per minute, it is called (normal) *sinus rhythm*. A sinus rhythm faster than 100 bpm is called *sinus tachycardia* (tachy = fast). This is usually caused by a benign condition in the body requiring an increased flow of blood, but it may be a sign of a more serious condition. A sinus rhythm slower than 60 beats per minute is called *sinus bradycardia* (brady = slow), and is common for young people and well trained athletes. If the change in rhythm is more than 10 % when slow and fast parts in an ECG are compared, the diagnosis is *sinus arrhythmia*.

Any heart rhythm that is not initiated by the sino atrial node is an *ectopic rhythm*. There are two basic types: (1) escape beats and rhythms and (2) premature beats and tachycardias. *Escape beats* appear when the sino atrial impulse is delayed or blocked so that latent pacemaker cells have an opportunity to fire; three or more consecutive escape beats are an escape rhythm. A *premature beat* occurs when an ectopic pacemaker fires early, before the sino atrial impulse has a chance to reach it. Two consecutive premature beats are called a salvo, and three or more, a tachycardia. There are several types of premature beats: *atrial premature beats* (APB), *AV junctional premature beats*(also called Nodal or junctional premature beats), *ventricular premature beats* and *premature ventricular contraction*.

Supraventricular tachycardia is a broad term which includes any supraventricular rhythm faster than 100 beats per minute. More specific diagnosis are listed in table **??**.

Atrial tachycardia is defined as a complex of three or more ectopic atrial beats, and in *flutter* the atria go even faster: the atrial rate is usually around 300 beats per minute, although it may range from 225 to 350. Atrial flutter is caused by a so-called *circus movement*: the impulse goes round and round in a circuit of conducting cells. *Atrial fibrillation* is also caused by circus impulses, but unlike atrial flutter the impulses follow various paths and frequently collide so that the atria do not really beat, but instead quiver erratically.

Another kind of beats are *fusion beats*, which are the result of ventricular depolarisation by two different pacemakers. Fusion beats are often a useful diagnostic clue in rhythm analysis.

class	*rhythm*
A.	Regular ventricular rhythm
	1. Sinus tachycardia
	2. Atrial tachycardia
	3. AV junctional tachycardia
	4. Re-entrant (reciprocal) supraventricular tachycardia
	5. Atrial flutter with fixed block
B.	Irregular ventricular rhythm
	1. Multifocal atrial tachycardia
	2. Atrial tachycardia with varying block
	3. Atrial with varying block
	4. Atrial fibrillation

Table 2.3: Supraventricular Tachycardia

2.7 ECG Analysers

There are 2 different types of (automated) ECG analysing systems [?] :

1. Continuous Cardiac monitoring in Intensive care units. Main goal is to detect potentially lethal rhythms.

2. Continuous monitoring by ambulatory (Holter) Recording. The signals are recorded over a long period of time, and are diagnosed afterwards (delayed). Due to the huge amount of data special attention must be paid to an efficient algorithm.

2.7.1 Cardiac Monitoring

Cardiac *monitoring* is used on patients who are likely to experience sudden changes in heart rhythm, and require immediate diagnosis and therapy should such changes occur. These situations include patients with acute myocardial infarction, patients undergoing general anaesthesia, and patients with any condition serious enough to warrant intensive care.

When cardiac monitoring is performed, a single lead is selected for continuous analysis. Since usually the electrodes are attached to the patient's chest (so called *modified limb leads*), the resulting complexes resemble those in a precordial lead. When the recording (positive) electrode is to the right of the sternum, the display is similar to V_l, which normally shows a negative QRS complex but is particularly useful for differentiating different types of bundle branch block. When the recording electrode is on the left chest a V_5-like pattern is the result.

2.7.2 Holter Monitoring

The conventional 12-lead electrocardiogram is intended to provide the interpreter with sufficient information to diagnose the cardiac rhythm and any disease involving one or more chambers of the heart. In some cases of abnormal heart rhythms (*arrhythmia*), the few beats shown in each lead are not enough for a definite diagnosis. This problem can be solved by taking long recordings (*Holter recordings*). Since the relationship between atrial and ventricular activity is often the key to diagnosing an arrhythmia, and since the QRS complexes are usually obvious in any lead, the rhythm strip should be made on a lead which best displays atrial activity. In most cases, this means lead II or V_l, but in all cases all 12 leads should be recorded first.

Chapter 3

Weightless Neural Systems

3.1 Pattern Recognition

The term pattern recognition encompasses a wide range of information processing problems of great practical significance, from speech recognition and the classification of handwritten characters, to fault detection in machinery and medical diagnosis. Pattern recognition tasks can be roughly divided into two classes: recognition of patterns in images and recognition of patterns in time series.

From the earliest days of neurocomputing, Artificial Neural Networks(ANN) have been recognised as being unusually well suited for performing pattern recognition tasks. Neural Networks can be regarded as an extension of the many conventional techniques which have been developed over several decades.

3.2 Artificial Neural Networks

The beginning of Artificial Neural Network research is often taken to be the 1943 paper of Warren McCullough and Walter Pitts [?]. This paper showed that even simple types of neural networks could, in principle, compute any arithmetic or logical function. Such a neural network is constructed of neurons, which fire when at least some minimum number of its inputs are active. This basic idea was inspired by how people thought the human brain worked. Since then many researchers have used, enhanced or altered their idea.

In general a Neural Network can be defined as follows:

Definition 3.1 A neural network is a *parallel, distributed information processing structure consisting of processing elements interconnected via unidirectional signal channels called connections. Each processing element has a single output connection that branches into as many collateral connections as desired; each carries the same signal. The processing element output can be of any mathematical type desired. The information processing that goes on within each processing element can be defined arbitrarily with the restriction that it must be completely local; that is, it must depend only on the current values of the input signals arriving at the processing element via impinging connections and on values stored in the processing element's local memory* [**?**].

A conventional pattern recognising neural network is tries to find the best boundaries between the classes of the training set. Neural networks based on the multilayer perceptron architecture do this by adjusting the weights between the neurons during the training phase.

A Neural Network algorithm consists of two phases: the training phase and the testing phase. During the first phase the network will be trained, under some training regime and with representative data, to perform its task. This means training patterns[1] will be fed to the network, and the network somehow tries to memorise them. There are several kinds of training regimes, but they mainly fall into one of these three categories: supervised training, unsupervised training and reinforcement learning.

The test phase is the phase in which the network is actually used. Data is fed in the network, some generalisation process takes place in the neural network, and the result is presented.

3.3 Preprocessing

Since neural neural networks can perform essentially arbitrary non-linear functional mappings between sets of variables, a single neural network could, in principle be used to map the raw input data directly onto the required final output values. In

[1] also referred to as training samples

practice, for all but the simples problems, such an approach will generally give poor results for a number of reasons [?].

For most applications it is necessary first to transform the data into some new representation before training the neural network. In many practical applications the choice of pre-processing will be one of the most significant factors in determining the performance of the final system.

In the simplest case, pre-processing may take the form of linear transformation of the input data, and possibly also the output data (sometimes referred to as *post-processing*). More complex pre-processing may involve reduction of the dimensionality of the input data. The fact that such dimensionality reduction can lead to improved performance may at first appear somewhat paradoxical, since it cannot increase the information content of the data, and in most cases it will reduce it. The improved performance is caused by the removal of *redundant* information in the input data.

Another important way in which network performance can be improved, sometimes dramatically, is through the incorporation of *prior knowledge*, which refers to relevant information which might be used to develop a solution and which is additional to that provided by the training data. Prior knowledge can be either incorporated into the network structure itself or into the pre-processing and post-processing stages.

One of the most common forms of pre-processing consists of a simple linear rescaling or transformation of the input variables. Another well known form of pre-processing is *feature extraction*, the filtering of important measurement from the data.

3.4 Weightless Systems

Weightless Neural Networks are based on a different approach than the 'conventional' neural networks. The basic idea is that the network is trained by storing the training samples in memory, rather than adjusting weights in order to fit the samples better. Weightless Neural Network find their roots in the n-tuple sampling machine introduced by Bledsoe and Browning in 1959 [?]. This n-tuple sampling machine was used for character recognition, using several n-bit vectors as input for the system. In such a n-bit vector a bit was set if a corresponding photo-cell detected a black spot on the input pattern. Weightless Neural Networks are also called RAM-nets or n-tuple classifiers.

3.4.1 The RAM-node

The RAM-node [?] is the basic component of a Weightless Neural Network. It is, as usual for a neural building brick, a very simple element (see figure ??). Its function is to determine if a bit vector is present in the used trainingset. In order to do so it uses a so called *look-up table*. This look-up table can easily be implemented in the conventional *R*andom *A*ccess *M*emory of a computer, which makes learning a one-shot memorisation task.

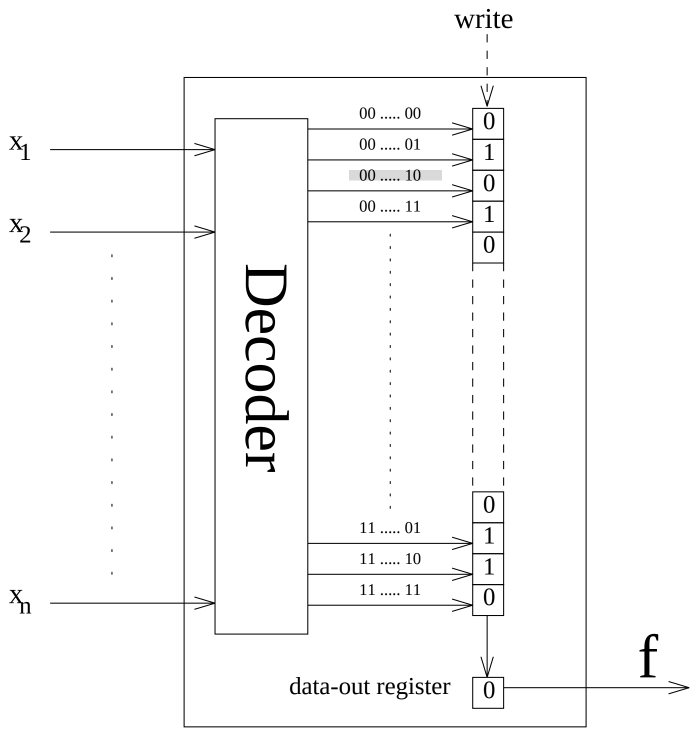

Figure 3.1: A RAM-node

Before the training begins the contents of the RAM are set to zero (FALSE). During the training phase the "write" signal in figure ?? is enabled. When a input vector is presented, the decoder treats this bit vector as an address of a memory location, and sets the contents of this address to '1' (TRUE). In order to be able to handle all possible bit vectors the size of the memory should be at least 2^n bits.

When during the test phase a bit vector is presented ("write" disabled), the contents of the memory address addressed by the bit vector is returned. This means it returns a '1' (TRUE) if the presented bit vector was *exactly* the same as a bit vector presented during the training phase, and a '0' (FALSE) otherwise. In figure **??** the pattern 00...10 is presented to the RAM-node, so the contents of the address 00...10 is returned as output (`f`).

A RAM node has no real generalisation: it has a binary output which merely tells if a pattern has occurred in the training data. Although this seems a disadvantage, it can easily be solved by combining several RAM-nodes.

3.4.2 Discriminator

In order to solve the problem of RAM-nodes having no generalisation, several of these RAM-nodes can be combined to a so-called *discriminator*. A discriminator consists of a layer of RAM-nodes organised as illustrated in figure **??**.

The most important feature of a discriminator is that it splits the input pattern into K n-sized tuples, each of which are used as the input for a RAM-node. In this way the input pattern of the discriminator is distributed over the memory of several RAM-nodes, instead of being stored in only one location.

The generalisation is obtained from introducing a *summing device*, denoted by the $\sum$ symbol in figure **??**. The function of this device is to sum up the outputs of all the RAM-nodes of that discriminator, and divide it by the number of RAM-nodes K. This gives the fraction of RAM-nodes that generated a '1' when input vector X was given to the discriminator:

$$r_j = \frac{1}{K} \sum_{i=1}^{K} f_{ji}(X) \tag{3.1}$$

The symbols used in equation **??** are explained in table **??**.

In this way the result r of the discriminator can be seen as the outcome of a membership function; it is a number between 0 and 1 which states how much pattern X resembles the patterns used in training set for the discriminator.

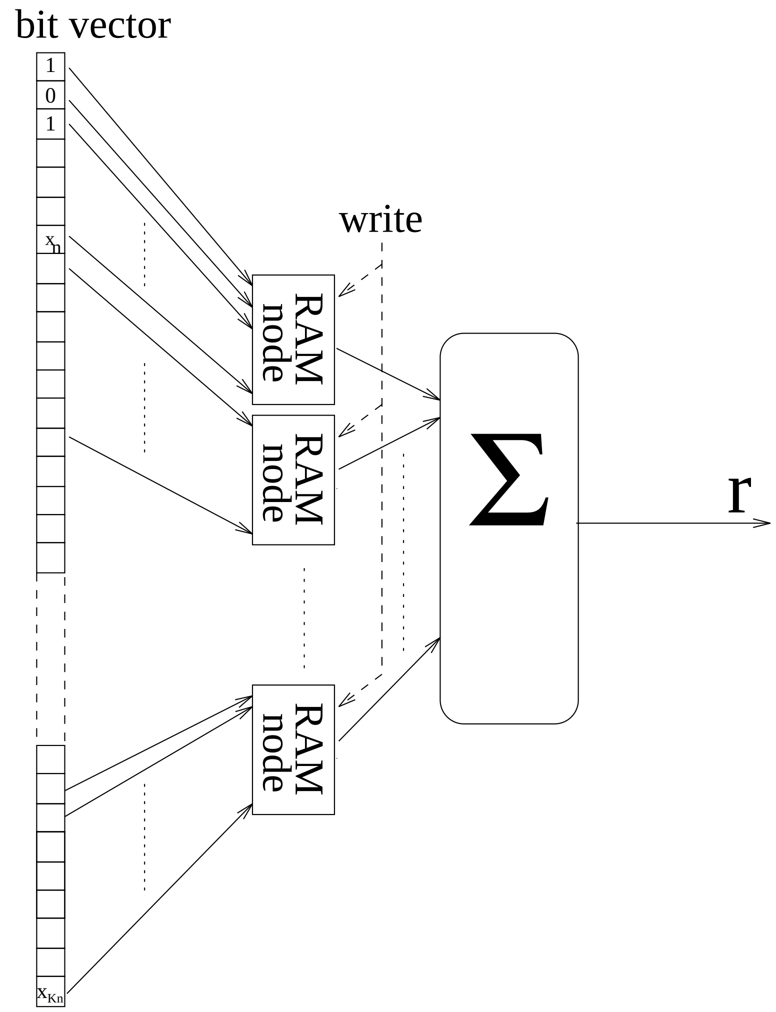

Figure 3.2: A discriminator

3.4.3 WISARD

WISARD is a binary pattern recognition system using several weightless discriminators. *WISARD* stands for *WI*lkie, *S*tonham and *A*leksander's *R*ecognition *D*evice. Originally, it was a hardware implementation of a multi-discriminator systems, with image recognition as it primary goal. Nowadays the term WISARD usually refers to a multi-weightless-discriminator architecture. Figure **??** shows a typical WISARD architecture. In fact the WISARD architecture resembles the standard architecture for a multi discriminator system.

A WISARD-system uses a simple, supervised training algorithm. When a bit vector and its class are presented, it only trains the discriminator assigned with the

symbol	*meaning*
n	tuple-size
K	number of ram-nodes
X	input vector
f_{ji}	output of ram-node i belonging to the j^{th} discriminator
x_i	the i^{th} element of X
r_j	the output of the j^{th} discriminator

Table 3.1: List of symbols

task to learn patterns belonging to that particular class. So if the system should classify bit vectors into three categories A, B and C, three discriminators should be trained: one for each category.

During the test phase the system presents the input vector to all trained discriminators. The result of the discriminators, (r_j for the j^{th} discriminator), are passed to a calculation unit. This unit determines which discriminator gives the highest output, and outputs the number or class of this discriminator. This is the class to which the input pattern is classified. It also calculates a measure of relative confidence C:

$$C = \frac{r_{max} - r_{secondmax}}{r_{max}} \tag{3.2}$$

The confidence is the relative difference between the highest and the second highest output of the discriminators.

3.4.4 A Comparison

Weightless Neural Networks fit definition **??** very well: they are built around a structure of parallel RAM-nodes. The binary output of the RAM-nodes do not branch out, but are only connected to the summing device. The RAM-node perform their task completely locally, only using their own local memory.

WISARD has the advantages of begin easily implemented in hardware and of being very fast during the training and recognition phase. It has found many industrial

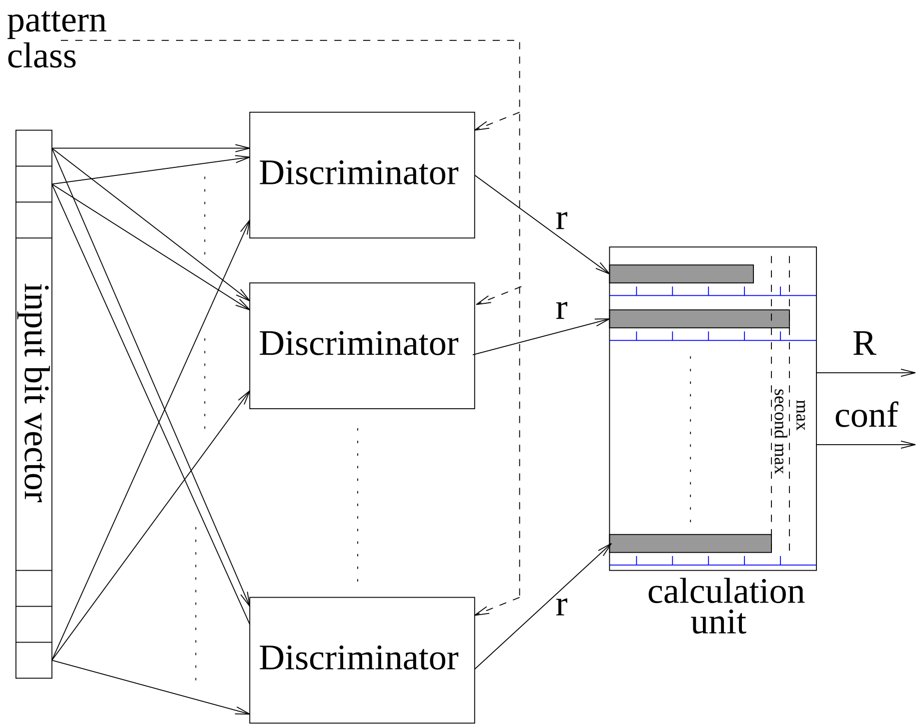

Figure 3.3: the WISARD architecture

implementations.

Weightless Neural Nets have been thoroughly tested by Richard Rohwer an Michal Morciniec [?]. They performed large scale experiments on the StatLog project datasets. These are 11 real world datasets which are used to test 23 other classification algorithms, including the most popular neural methods. The results showed that the n-tuple classifier method is a viable competitor to more popular methods due to its speed, simplicity and accuracy on the majority of a wide variety of classification problems. The n-tuple method score well on 6 of the 11 datasets, and the cause of failure on the others was identified as being inherent with the data and the way of coding the data.

Chapter 4

The ECG Data

4.1 The Data

The data used for this project comes from the MIT-BIH Arrhythmia Database CD-Rom[**?**]. This database is maintained by the Harvard-MIT Division of Health Sciences and Technology and contains over 200 hours of ECG recordings. The source of the ECG's is a set of over 4000 long-term Holter recordings that were obtained by the Beth Israel Hospital Arrhythmia Laboratory between 1975 and 1979. Approximately 60% of these recordings were obtained from in-patients. The main database contains 23 records (numbered from 100 to 124 inclusive with some numbers missing) chosen at random from this set, and 25 records (numbered from 200 to 234 inclusive, again with some numbers missing) selected from the same set to include a variety of rare but clinically important phenomena that would not be well-represented by a small random sample of Holter recordings. Each of the 48 recordings is slightly over 30 minutes long. The subjects were 25 men aged 32 to 89 years, and 22 women aged 23 to 89.

Records in the second group were chosen to include complex ventricular, junctional, and supraventricular and conduction abnormalities. Several of these records were selected because of features of the rhythm, QRS morphology variation, or signal quality.

Figure **??** shows a sample of a ECG recording from the database. The records contain two leads: in most records, the upper signal is a modified limb lead II (MLII), obtained by placing the electrodes on the chest. The lower signal is usually a modified lead V1 (occasionally V2 or V5, and in one instance V4); as for the

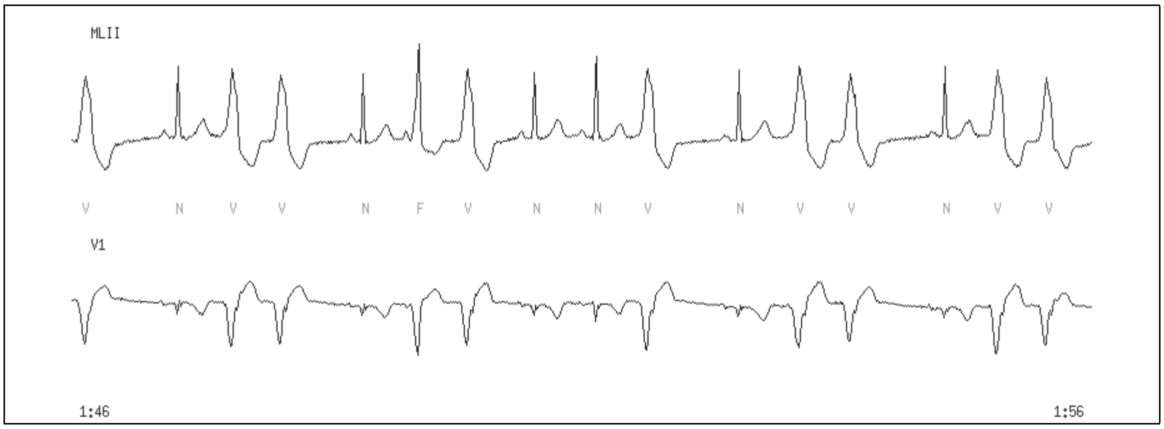

Figure 4.1: A sample of record 208

upper signal, the electrodes are also placed on the chest. This configuration is routinely used by the BIH Arrhythmia Laboratory. Normal QRS complexes are usually prominent in the upper signal. Normal beats are frequently difficult to discern in the lower signal, although ectopic beats will often be more prominent. A notable exception is record 114, for which the signals are reversed. Since this happens occasionally in clinical practice, arrhythmia detectors should be equipped to deal with this situation.

The original recordings were made analogue on two-channel recorders. During the digitisation process the analogue recordings were played back (sometimes at a speed twice real time), and digitised at sample rate of 360 Hertz. In this process several (minor) artifacts due to tape speed variations and mechanical frequencies were introduced. The resolution is 11 bits over a ± 5 millivolt range. Sample values thus range from 0 to 2047 with the value of 1024 corresponding to zero volts.

An initial set of labels was produced by a simple slope sensitive QRS detector, which marked each detected event as a normal beat. Then each of these marked records were given to two cardiologists, who worked on the independently. The cardiologists added additional beat labels where the detector missed beats, deleted false detections, and changed label for abnormal beats. They also added rhythm labels, signal quality labels and comments. A list of the labels used can be found in Appendix **??** on page **??**.

4.2 Record 208

The main signal used in this thesis is the record of patient 208. This particular record was selected because it contains more than two classes, it has some noisy periods and due to the availability of results obtained from other classification methods.

The patient from whom this ECG was recorded was a woman aged 23. The two leads are MLII and V1 (see section **??**). No medication was prescribed at the moment of recording. Figure **??** shows a small part of the signal.

Table **??** shows an overview of the type of beats that occur in record 208. SVPC stands for a supraventricular premature beat, PVC for a premature ventricular contraction beat, and Fusion PVC for a fusion of a ventricular and a normal beat.

Beats	*Before 5:00*	*After 5:00*	*Total*
Normal(N)	279	1307	1586
SVPC (S)	-	2	2
PVC (V)	168	824	992
Fusion PVC (F)	71	301	372
Unclassifiable (Q)	-	3	3
Total	518	2437	2955

Table 4.1: beats in record 208

4.3 An Analysis

In order to make a classification of beats, it is important to know whether there is some inherent clustering in the data. If this is not the case this means that the beats of different classes resemble each other too closely, or the data is completely random; automated classification will be a difficult and error prone task. A good way to see if data has some inherent clustering is to visualise it. Of course problems arise if the data has more than, say, 3 dimensions. Several algorithms have been invented in order to solve this problem. Here two multi-dimensional scaling algorithms have been applied on the ECG data contained in record 208: Sammon Mapping and Kohonen's Self Organising Map. The algorithms use unsupervised training of a set of 2-dimensional points and a set of n dimensional vectors (where n is the dimension of the input vectors) respectively.

Both of the mapping algorithms are included in SOM_PAK, the Self-Organising Map Program Package. This package is developed by the Helsinki University of Technology, and can be obtained from their ftp site: *cochlea.hut.fi* (130.233.168.48), from the directory */pub/som_pak*.

4.3.1 Sammon Mapping

The first algorithm used is that of John W. Sammon jr., as described in [**?**]. The algorithm is based upon a point mapping of N vectors from the $\mathcal{R}^n$-space to a lower-dimensional space such that the inherent structure of the data is approximately preserved under the mapping. The approximate structure preservation is maintained by fitting N points in the lower-dimensional space such that their interpoint distances approximate the corresponding distances in the $\mathcal{R}^n$-space .

Suppose we have N vectors $X_i \in \mathcal{R}^n$, $i = 1...N$ and corresponding to these we define N vectors in the 2-dimensional space $\mathcal{R}^2$, designated Y_i, $i = 1...N$. Let the distance[1] between the vectors in the $\mathcal{R}^n$-space defined by $d^*_{ij} = ||X_i, X_j||$ and distance between the corresponding vectors Y_i and Y_j in the two dimensional space be defined by $d_{ij} = ||Y_i, Y_j||$. Now we compute all the 2-dimensional space interpoint distances d_{ij}, which are then used to define an error E, which represents how well the present configuration of N points in the 2-dimensional space fits the N points in the $\mathcal{R}^n$-space:

$$E = \frac{1}{\sum_{i<j}[d^*_{ij}]} \sum_{i<j}^{N} \frac{[d^*_{ij} - d_{ij}]^2}{d^*_{ij}} \tag{4.1}$$

The next step is to change the configuration of the vectors in the 2-dimensional space, in order to decrease the error. A steepest descent procedure is used to search for the minimum error.

[1] Any distance measure could be used. Here the Euclidean distance measure $||x - y||$ for two points $x, y \in \mathcal{R}^n$ is chosen.

4.3.2 Kohonen's Self Organising Map

An other technique is the Kohonen topographic feature map, also called *self-organising feature map* [**?**]. This algorithm leads to placement of a set of prototype vectors in input space, each of which corresponds to a point on a regular grid in a (usually two-dimensional) feature map space. When the algorithm has converged, prototype vectors corresponding to nearby points on the feature map grid have nearby locations in input space. This leads to a number of applications for this algorithm including the projection of data into a two-dimensional space for visualisation purposes [**?**].

The Kohonen mapping used here, is a mapping from a high-dimensional data space $\mathcal{R}^n$ onto a regular two dimensional array of points (nodes). With every node i, a parametric reference vector $m_i \in \mathcal{R}^n$ is associated. An input vector $x \in \mathcal{R}^n$ is compared with the m_i, and the best match is defined as response: the input is thus mapped onto this location. The best-matching node is usually defined by the smallest Euclidean distance $||x - m_i||$, but it can be compared with m_i using any distance metric.

Initially all the m_i-vectors are set to random values. During the unsupervised training the value of m_i vectors are updated according equation **??**:

$$m_i(t+1) = m_i(t) + h_{ci}(t)[x(t) - m_i(t)], \tag{4.2}$$

where t is an integer, the discrete-time coordinate, and h_{ci} is the so-called *neighbourhood kernel*, a function defined over the lattice points. The kernel used here refers to a neighbourhood set of array points around node c. Let this set be denoted $N_c(t)$, whereby

$$h_{ci} = \begin{cases} \alpha(t) & \text{if } i \in N_c(t) \\ 0 & \text{if } i \notin N_c(t) \end{cases} \tag{4.3}$$

The initial value of the *learning rate* $\alpha(t)$ is defined and decreases linearly to zero by the end of training. The initial value of the neighbourhood $N_c(t)$ is also defined and decreases linearly to one (in the end only the nearest neighbours are trained).

4.3.3 Preprocessing

As input for the two algorithms the MLII lead of record 208 was used. First the signal was resampled to a sampling frequency of 90 Hertz. Then for each beat 75 sample values were used: 37 before and 37 after the R-peak, and the R-peak itself. This range corresponds to approximately 0.8 seconds, which is the duration of a beat at a heart rate of 75 beats per minute (see table **??**). The resampling had to be performed in order to get vectors small enough to use with the mapping packages.

This way a set training samples was obtained, which was used as source of the inputs for the unsupervised training of both algorithms. Three training sets were used: the first containing the first 300 beats of record 208, the second containing 100 beats of each class (300 in total), and the third containing the first 500 beats of the record. Table **??** shows the number of beats in each class for the sets.

Set	*N-beats*	*F-beats*	*V-beats*	*total*
A	161	37	102	300
B	100	100	100	300
C	269	70	161	500

Table 4.2: used training sets

4.3.4 Results

In this sections the results are shown from application of the two methods described earlier. The results are obtained using the SOM_PAK package and visualised using '*gnuplot*'. The cluster borders in figures **??** and **??** are manually added to increase the visual effect of the clustering

All the results were obtained using an $\alpha(0)$ of 0.05 and an initial $N_c(0)$ of 10 during the first 1000 iterations (in order to roughly order the mappings) and an $\alpha(0)$ of 0.03 and a $N_c(0)$ of 3 during the following 10000 iterations (the fine tuning). For the Kohonen mapping a grid of 12 by 8 nodes was used.

Both the Sammon mapping and Kohonen's SOM mapping were applied to dataset A. Figures **??** and **??** show that there is some clustering in the data. The problem with this dataset is that it is difficult to see in the Sammon figure, whether the F

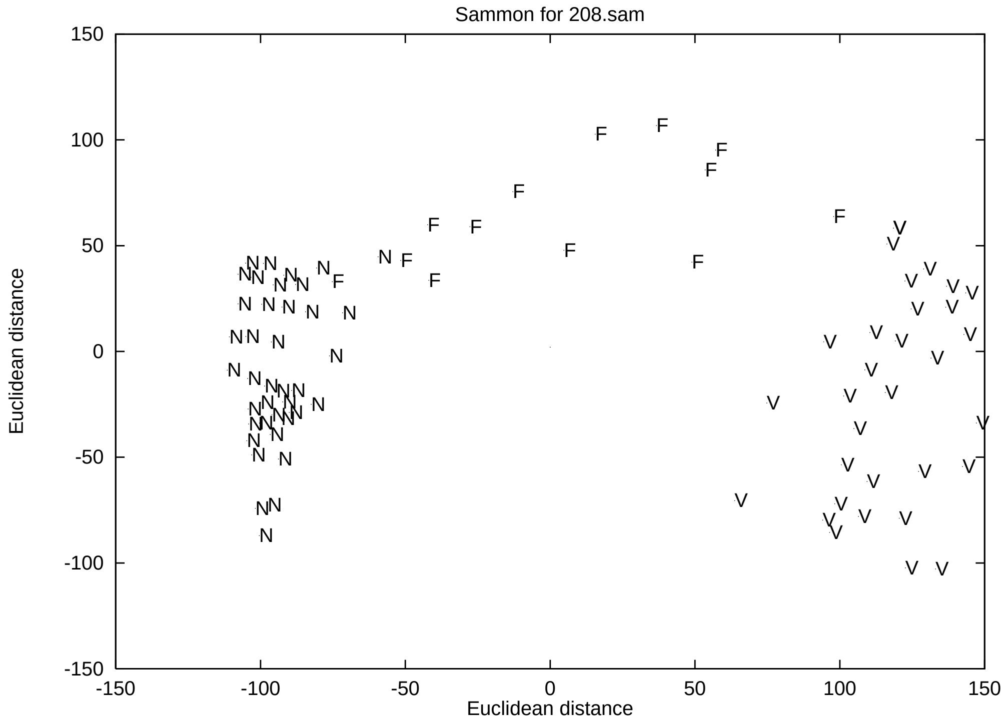

Figure 4.2: A Sammon mapping of signal 208, using the first 300 beats of the signal

beats are really clustered, or are merely some floating points. The reason for this seems to be the unbalanced number of beats in each class.

The Sammon mapping of dataset B (figure **??**) shows that the F beats are clustered, although their clustering is less restricted than for the N-cluster and the V cluster. Kohonen's SOM mapping of dataset B (figure **??**) resembles the SOM mapping of data set A, although the N beats are "pressed against the wall" by the F cluster. The V cluster remains approximately the same (probably because the number of V beats are about the same in the two data sets).

The Sammon mapping of dataset C (figure **??**) shows that although the clustering remains intact, adding samples to the training set (set A is a subset C), and different randomisation for the initial value for the 2 dimensional Y_i vectors, does have a great influence on the state to which the trained system converges. The clusters seems to move around each other, but the distances between the clusters stay about the same.

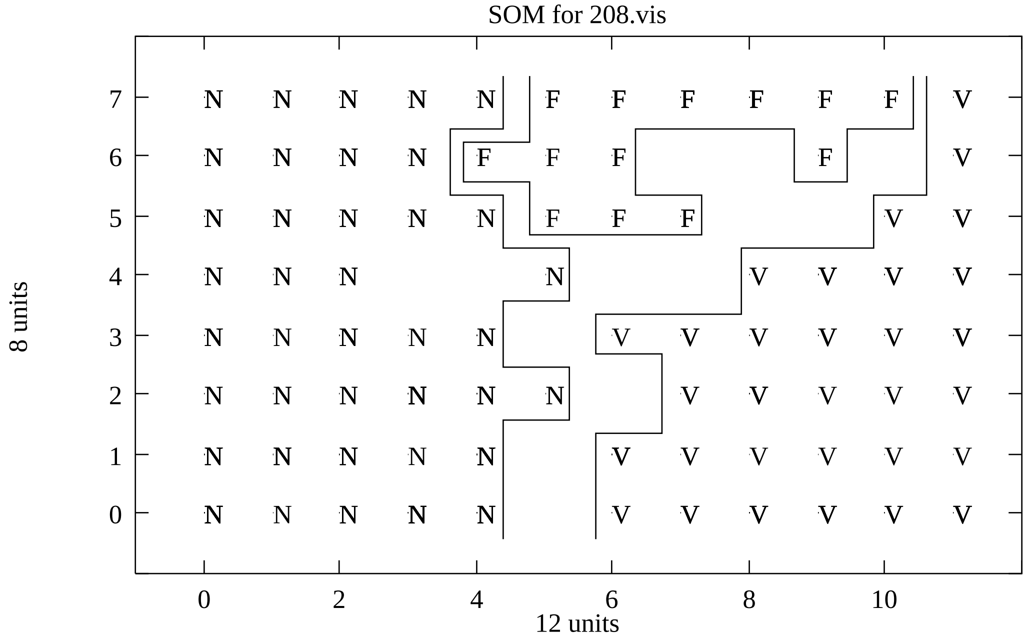

Figure 4.3: A SOM mapping of signal 208, using the first 300 beats of the signal

4.3.5 Conclusions

Both the algorithms show that there is some inherent clustering in the data. Accordingly classification of the beats should be possible. Neural network should be able to find some borders between the classes in the multi dimensional space, using the raw data as their input.

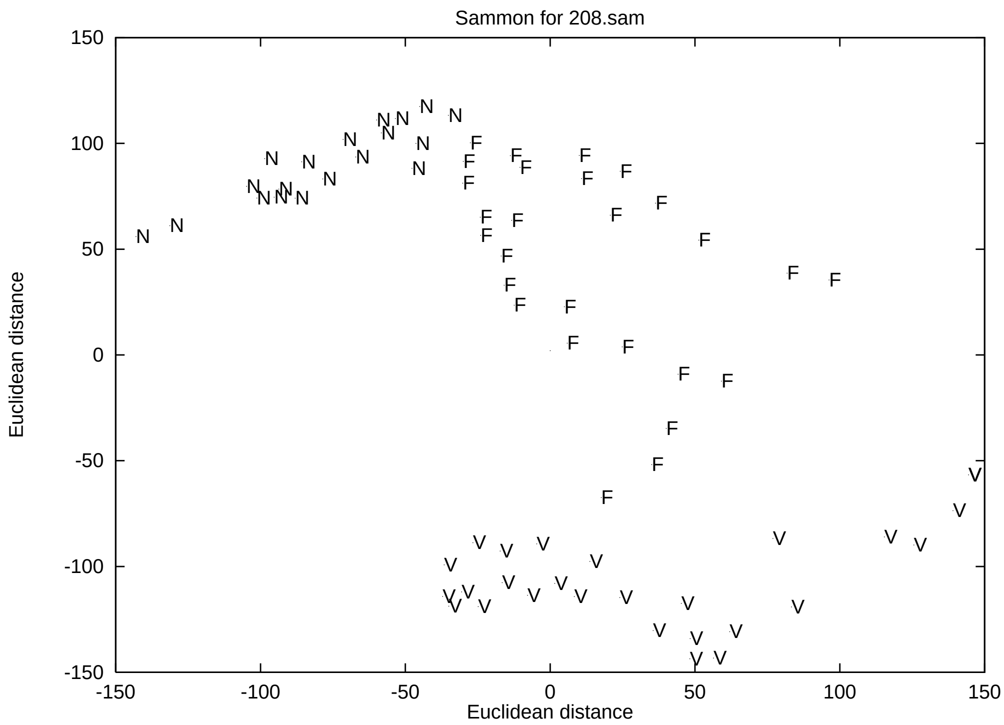

Figure 4.4: A Sammon mapping of signal 208, using 100 beats of each class

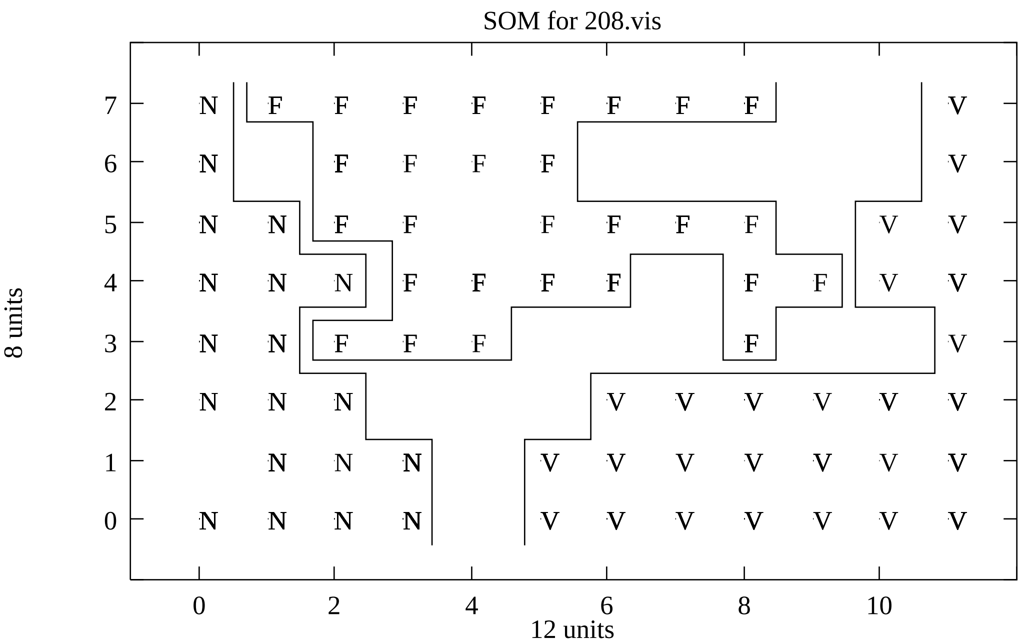

Figure 4.5: A SOM mapping of signal 208, using 100 beats of each class

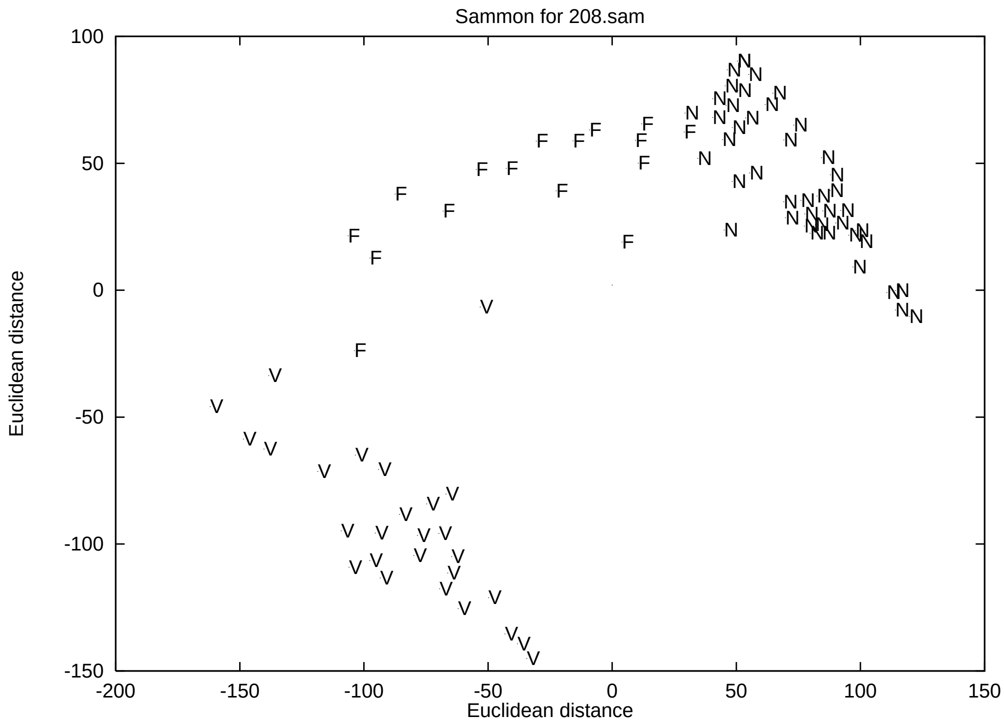

Figure 4.6: A Sammon mapping of signal 208, using the first 500 beats of the signal

Chapter 5

System Design

The basic system described in this section is one designed for the classification of heart beats. This task should not be confused with the diagnosis of rhythms to find any disease related with the heart; this is a research field in itself. One might think of this system as a part of a diagnosis system; the outputs of the analysis system can be used as input for an Expert System, which could tell something about the status of the patients heart.

5.1 The Initial Design

The system is based on the WISARD type multi-discriminator architecture: for each relevant class of beats a discriminator is trained. Figure **??** shows the design of the system.

The classification of ECG beats consist of two parts: the first is the preprocessing part, the second the Weightless Neural Network part. The preprocessing part is mainly the extraction of a beat from the record and coding this beat into a bit string. A *thermometer coding* algorithm will be used in order to feed the data into the discriminators.

During the supervised training phase of the neural part each discriminator learns a specific kind of beat. During the test phase the input vector will be fed into all discriminators and the discriminator with the highest output determines the type of the bead fed into the system.

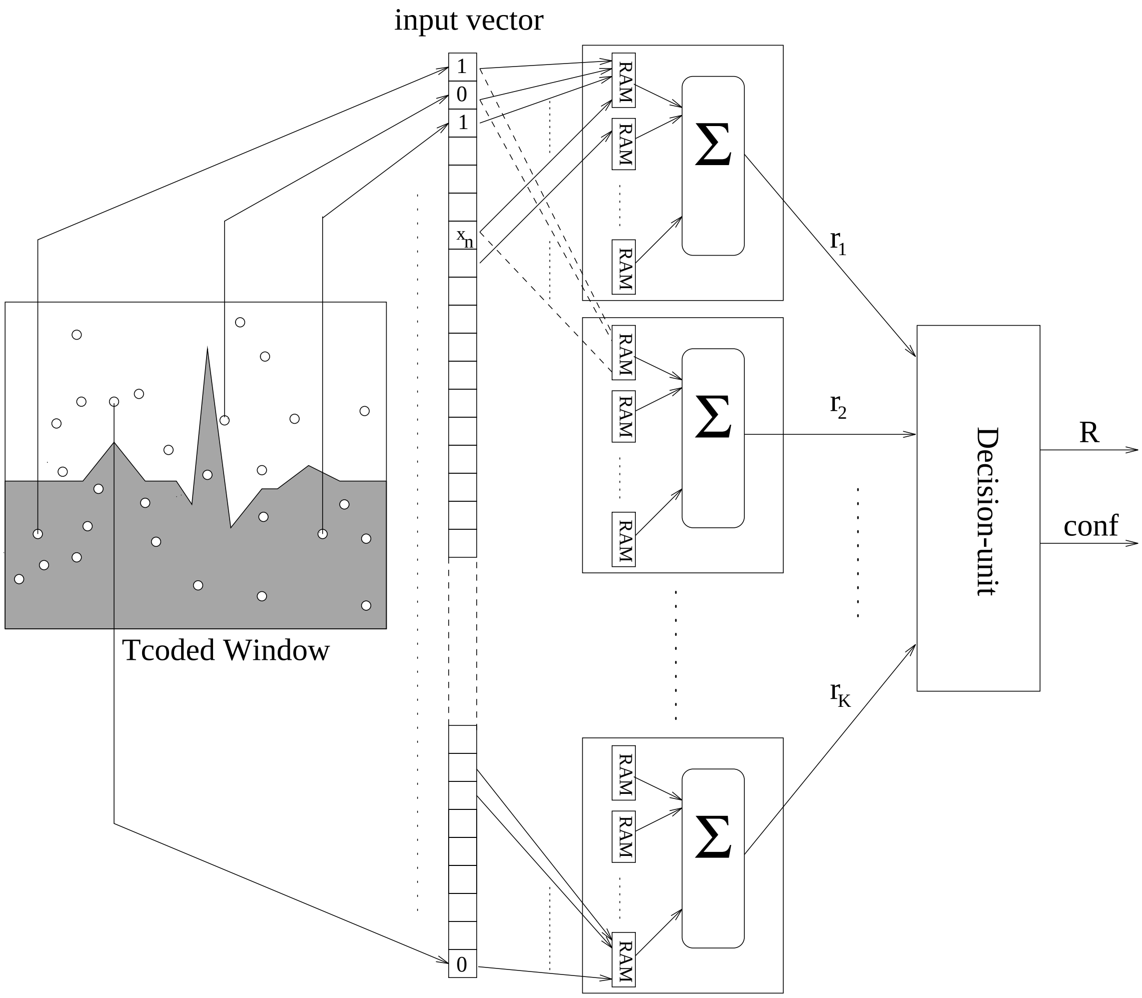

Figure 5.1: The System Design

5.2 Preprocessing & Coding

The basic idea of the coding used here is to create an image of the the beat, put an input retina over this image, and use this retina to fill a bitmap. This image can be seen as a window moving over the the total recorded signal.

5.2.1 The Input Window

One beat is taken to be a fixed number of sample values (or, equivalently, milliseconds). The number of samples is called `wsize`, from window-size. The default value of `wsize` was taken to be 300; this resembles 0.8 seconds of the signal, and this is the duration of one beat at a normal rate of 75 beats per minute[1].

The best feature to pick one beat out of the total record is to detect the QRS complex, and take this as a reference point. Here a number of sample values before and a number of sample values after the QRS complex are taken. The ratio of the number of samples before and after the QRS-complex is called `beatratio`, and is one of the parameters of the system.

The resolution in the y-direction of the window can be taken as $2^{11} = 2048$, but in order to reduce the size of the window the signal is scaled to a smaller resolution called `wres`, the window resolution. As a default value for `wres`, 200 was taken. All the signal values are scaled to the nearest integer in the range of this `wres`. In formula:

$$x_T = \left\lfloor \frac{x}{2^{sr}} \times wres + \frac{1}{2} \right\rfloor \tag{5.1}$$

where x_T is the T-coded value of sample value x and `sr` the sampling resolution. $\lfloor ... \rfloor$ denotes the biggest integer value smaller than or equal to the value between the delimiters[2].

5.2.2 The Retina

The beat window is covered by a retina. This retina is a array of input points. Each point in the retina is related to one bit in the input vector of the neural network. If a retina point lies below the signal in the window, then the corresponding bit in the vector is set to 1; if it lies above the signal, the bit is reset to 0. This method is called *thermometer coding*[3] because it resembles the way mercury points out a temperature in a thermometer: black ("ones") under, and white ("zeros") above the value.

The points of the retina are uniformly random connected with the bits in the input vector, and cover a percentage (`coverage`) of the window points. The parameters `wsize`, `wres` and `coverage` determine the size of the input vector: `wsize`

[1] This is the case for the MIT-BIH ECG records: these are sampled at a frequency of 360 Hz. Other frequencies required longer or short window sizes.

[2] The $\frac{1}{2}$ is added in the formula to make the function of the $\lfloor ... \rfloor$ delimiters rounding to the nearest integer, rather than rounding to the biggest integer smaller than the value.

[3] For convenience also referred to *T-coding* or *tcoding*.

and `wres` form a grid of `wsize` $\times$ `wres` points, and `coverage` determines how many of these point are actually connected to a bit in the input vector. So if `wsize` $= 300$, `wres` $= 200$ and `coverage` $= 50\%$, the length of the input vector is $300 \times 200 \times (50/100) = 30,000$ bits.

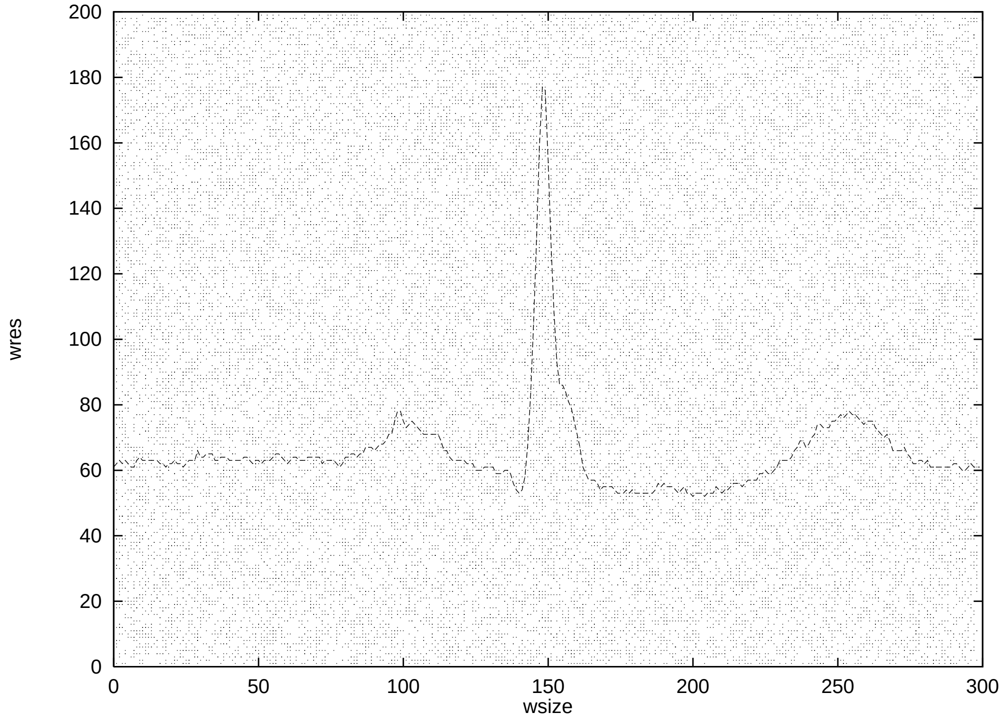

Figure 5.2: A windowed beat with uniformly random retina.

Whether the discriminators have identical input connections or not hardly matters. Each discriminator is trained to its own class of patterns, and therefore whether it is wired similarly to or differently from other discriminators is not of much consequence [**?**].

5.3 Enhancements

5.3.1 The Window

The data from the MIT-BIH data base has a binary resolution (`sr`) of 11 bits. Inspection of the data showed that not all of the $2^{11} = 2048$ possibles values are used. For record 208 the minimum sample value is 327 and the maximum 1754. Table **??** shows that for this record more than 99% of the value lie between 700 and

1399. This means that the window has a lot of 'white-space'; areas which contain no relevant information.

range	*frequency*	*range*	*frequency*
0-99	0	1000-1099	127714
100-199	0	1100-1199	26806
200-299	0	1200-1299	27558
300-399	6	1300-1399	7982
400-499	5	1400-1499	1404
500-599	47	1500-1599	235
600-699	650	1600-1699	129
700-799	4240	1700-1799	74
800-899	67449	1800-1899	0
900-999	385701	1900-2047	0

Table 5.1: sample values occurring in signal 208

In order to remove this white-space, equation **??** can be changed to:

$$x'_T = \left\lfloor \frac{x - T_{\min}}{T_{\max} - T_{\min}} \times wres + \frac{1}{2} \right\rfloor \tag{5.2}$$

where $\mathtt{T}_{\min}$ is the lower bound for the sample values and $\mathtt{T}_{\max}$ the upperbound. This equation rescales the sample values to fit the window resolution `wres` more closely. When $\mathtt{T}_{\min} = 0$ and $\mathtt{T}_{\max} = 2^{\mathtt{sr}}$ the coding will be the same as in equation **??**.

5.3.2 The Retina

The uniformly randomised retina described above doesn't incorporate prior knowledge about the ECG signal. Most of the information in the signal is gathered around the base line, so this should be the place where the system "looks", in other words: where most of the retina points are selected.

To solve this problem for a certain amount of retina points the y-value is distributed normally among the baseline. The x-values are still distributed uniformly random. A random variable is said to be normally distributed with mean μ and variance σ^2, (notation: $X \sim \mathcal{N}(\mu, \sigma^2)$) if the density is:

$$f(x) = \frac{1}{\sqrt{2\pi}\sigma} e^{-(x-\mu)^2/2\sigma^2} \qquad -\infty < x < \infty \tag{5.3}$$

$\mathcal{N}(0,1)$ is called the *standard normal distribution*. Here the y-value of the retina points are distributed normally with the baseline value as mean and a parameter `cutoff` as a "variance"[4]. The parameter `dist-ratio` is the ratio between the number of points with normal distributed y-value and the number of points with uniform random distributed y value. If `dist-ratio` is 0 all points have normal distributed y-values and if `dist-ratio` is 1 the retina is still the old type of retina (as in figure **??**). Figure **??** show a retina with `cutoff`=50 and `dist-ratio`=0.3.

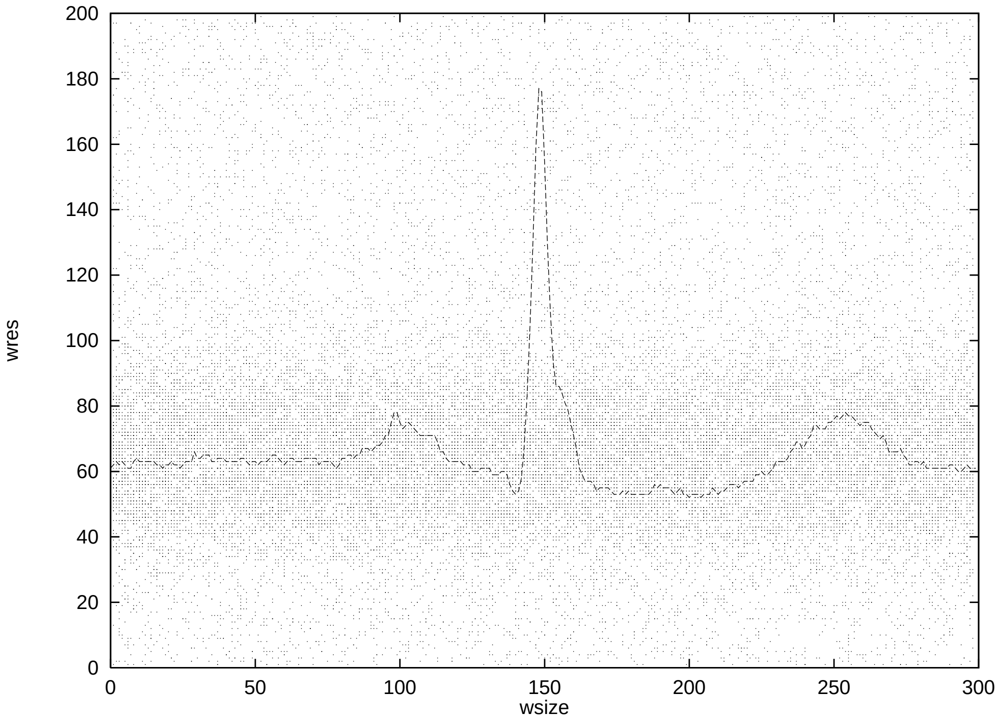

Figure 5.3: A windowed beat with partly normal distributed retina. `ratio` = 0.3

[4]In fact a standard normal distribution is used, but if $x \sim \mathcal{N}(0,1)$ and $y = \tau x + \eta$ then $y \sim \mathcal{N}(\eta, \tau)$. `cutoff` is approximately 3 times the variance for programming reasons.

5.3.3 QRS Filter

Section **??** mentions briefly that the QRS complex is the best feature to get hold of a beat out of the record. The QRS complex is a prominent feature in some leads of an ECG recording, but it is a difficult task to extract all the QRS complexes correctly, especially when the pattern shows irregular and abnormal beats. W.A.H. Engelse and C. Zeelenberg developed a QRS detector based on low pass filtering [**?**]. This algorithm keeps track of the number of slopes in the signal, and the time passed.

Since QRS detection is error prone for signals with irregular and abnormal beats it is common practice for researches of automated ECG analysis to use the QRS times stored in the annotation files of the datasets. Although this is information that is normally not available, expecially not during the test phase of the system, this practice allows focusing on the classification problem rather than on the feature extraction.

5.3.4 Fit to Axis

The position electrodes might change when the patient under study breaths or moves. These changes might cause the baseline of the beats in the ECG recordings to deviate from the horizontal, to be elavered of depressed. This can be an obstacle for good classification or, for example, QRS detection.

To correct this problem each beat is translated so that the average lies on a certain fixed point. In formula:

$$x_{new}(t) = x_{old}(t) - \overline{x} + axis \tag{5.4}$$

where $\overline{x}$ is:

$$\overline{x} = \sum_{i=1}^{wsize} x_i \tag{5.5}$$

$axis$ is the y-value of the horizontal line on which the average of the beat is fitted. Approximately $\frac{2}{5}$ of the beat lies under the baseline and the remaining $\frac{3}{5}$ lies above it (see table **??**: the baseline is 1024). This is why $axis$ is chosen to be $\frac{2}{5}$ of `wres` (the translation is performed after t-coding the signal, if it would have been done before, $axis$ should have been $\frac{2}{5}$ of 2^{sr}, the number of possible sample values).

5.4 Parameters

For the system the parameters introduced in the previous sections can be changed. Table ?? shows the parameters for the system and some bounds for the possible values.

parameter	*meaning*	*values*
n	n-tuple size	1 - 16
`J`	number of discriminators	2 - 10
classes	see Appendix ??	
`wres`	number of bits for the tcoding	±200
`wsize`	number of samples per beat	100 - 500
$\mathtt{T}_{\mathrm{min}}$	minimum bound cutoff	0 - 700
$\mathtt{T}_{\mathrm{max}}$	maximum bound cutoff	1400 - 2047
`beatratio`	placement of beat in window	0.3 - 0.7
`coverage`	percentage of input space coverage	1 - 200
$\mathtt{t}_{\mathtt{train}}$	number of seconds to train[5]	300
`dist-ratio`	ratio for combination	0.0 - 1.0
`cutoff`	"variance" for normal distribution	± 50
`seed`	seed for retina distribution	

Table 5.2: used parameters

5.5 Implementation

The system was implemented in C++, in order to make it as easy as possible to make changes to the system. The basic components, like bitvector, RAM-node, discriminator and signal, were implemented as object classes.

The reading and writing of the ECG signals and its annotation files was provided by C-libraries that came with the MIT-BIT database distribution. Most of these functions were embedded in the C++ classes.

[5] This is the number of seconds from the record, not the actual number of seconds.

Some of the design element mentioned earlier were not ‘physically’ implemented; for example no image object of a beat was created. These elements were introduced to make the design of the system more clear.

The system was implement for the SUN platform, but using the GNU g++ compiler makes it possible to recompile the program for other platforms.

Chapter 6

Tests & Results

This chapter contains the main results of this research. The results are based on over 1200 experiments. The experiments focus on the influence of the basic 'neural' parameters (length of the input vector, n-tuple size) and the retina type on the results. The length of the input vector is determined by the `coverage`, `wsize` and `wres` parameters.

Initial investigation with the other parameters showed that parameters `wres`, $\mathtt{T}_{\mathrm{min}}$ and $\mathtt{T}_{\mathrm{max}}$ do not seem to have much effect on the results, as long as they stay within 'normal' proportions. The results of these initial 'playing around' experiments are not presented, but their effect lies in the chosen values of the parameters in the subsequent experiments.

6.1 The Tests

The basic idea of the test is to train the network, test it, and see how many misclassifications it makes, and what the confidences are. The experiments performed are based on the method described by George Moody [?]. This method is the recommended evaluation protocol for ECG Analysers of the Association for the Advancement of Medical Instrumentation (AAMI). It states that for the MIT-BIH database records the the training patterns should be in the first 5 minutes of the signal, and the test patterns in the remaining 25. During the testing phase, the annotation files may be used to extract single beats from the record. This is because the extraction of QRS-peaks out of the total recorded signal is a research field in itself.

6.2 The Training Set

This section shows the results of the preprocessing of the data. Figures ??, ?? and ?? (pages ??, ?? and ??) show beats from the first five minutes of record 208, the reference record. Figure ?? shows the normal beats (N), figure ?? shows the ventricular premature contraction beats (V) and figure ?? shows the fusion beats. The latter beats are a fusion of ventricular and normal beats.

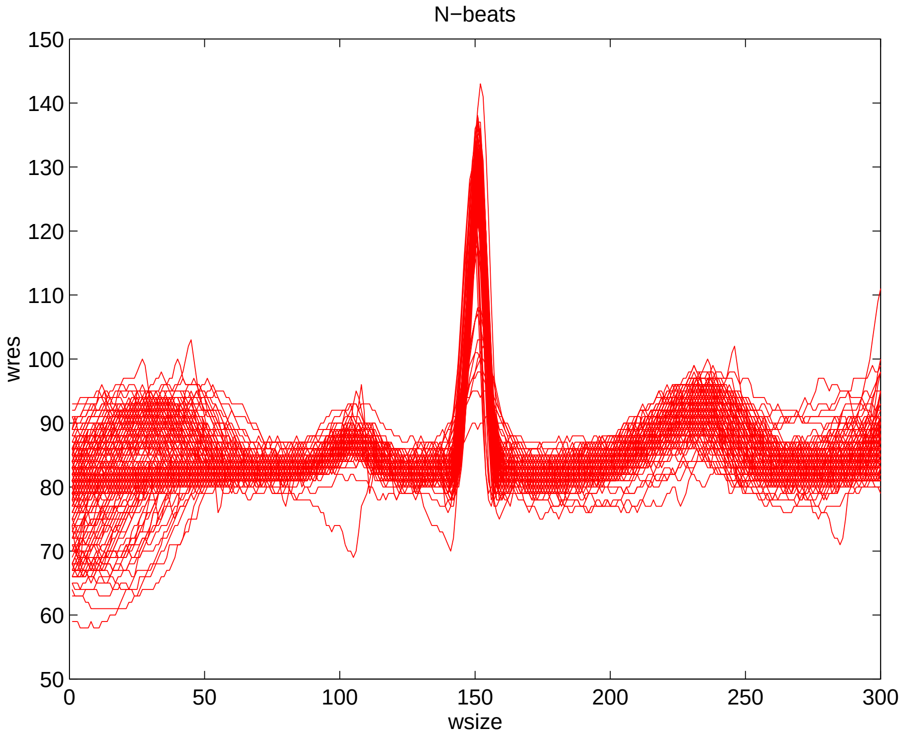

Figure 6.1: The Normal beats in the training period

The figures are obtained by using the following parameters for the coding:

$$\begin{aligned} \texttt{wsize} &= 300 \\ \texttt{wres} &= 200 \\ \texttt{T}_{\min} &= 300 \\ \texttt{T}_{\max} &= 1800 \end{aligned}$$

Note that the figures only show the t-coded beats from 50 to 150. Examination of the whole pattern (see table ??) shows that the sample values of record 208 lie between 327 and 1754. That is why $\texttt{T}_{\min}$ and $\texttt{T}_{\max}$ are chosen 300 and 1800 respectively.

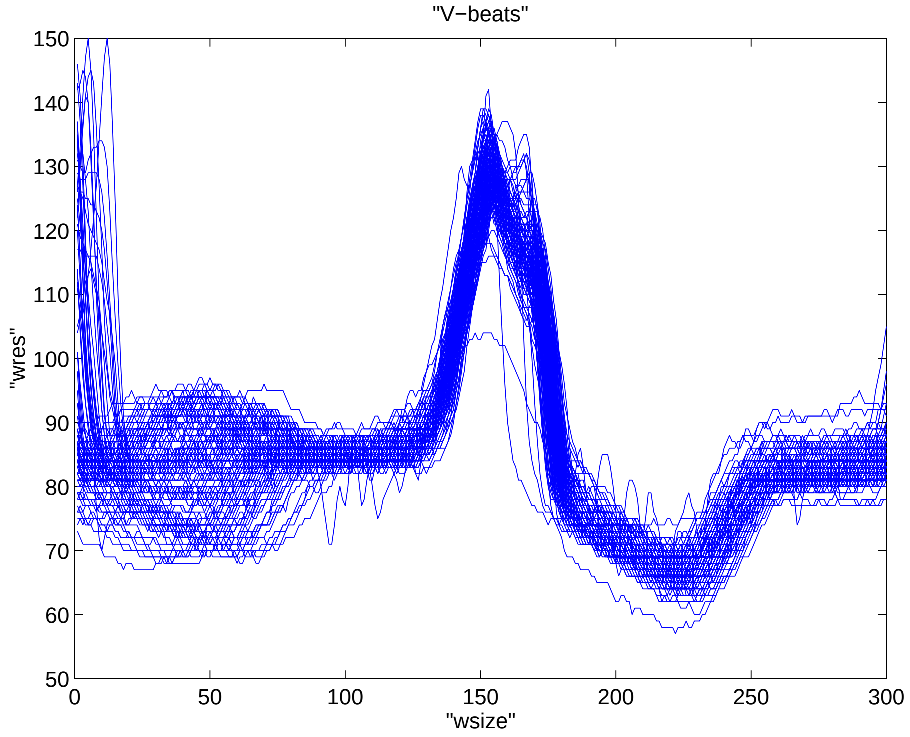

Figure 6.2: The Premature ventricular contraction beats in the training period

Apparently the beats containing these sample values are not in the training period of the record.

The figures illustrate the differences between the classes of patterns: figure **??**, with the ventricular premature contractions, shows that because of the premature contraction of the ventricles the QRS-peak preceding beat sometimes appears sometimes at the left side in the figures. This results from the the fact that the window is placed around the QRS peak, which is related to the ventrical systole. The figure also shows the absence of the P wave compared with the normal beats: this is obscured by the QRS complex.

Figure **??** shows that the fusion beats most of the time have a depressed ST-segment. Note that the first 'waves' are not part of the shown beats, but are the T waves of the previous beat, and that there appear some QRS complexes on the right side of the figure. Both of these effects are because the duration of a fusion beat is normally shorter than a normal or ventricular premature beat. This can be seen in the sample of record 208 on page **??**.

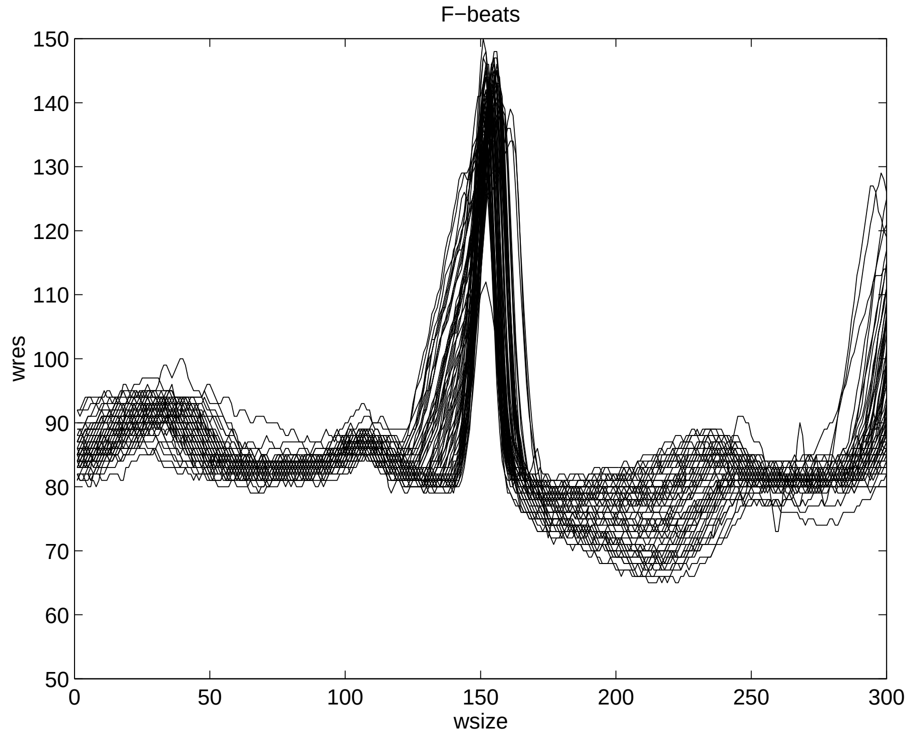

Figure 6.3: The Fusion beats in the training period

6.3 Test 1: The Uniform Random Retina

This section describes the results of the experiments with the basic system, when the uniform random distributed retina (see figure **??**) was used. The system is trained on the first 5 minutes of record 208 to recognise N, V and F beats. Figure **??** shows the average misclassifications against the used n-tuple size. The experiment were performed for `coverage` = 25%, 50% , 75% and 100%, and n-tuples ranging from 1 to 14.

The rest of the parameters are:

`wsize`	=	300
`wres`	=	200
$\mathtt{T}_{\mathrm{min}}$	=	300
$\mathtt{T}_{\mathrm{max}}$	=	1800
`beatratio`	=	0.5

Figure **??** shows that the number of misclassifications decreases when the n-tuples size increases. This is what was expected, up to a certain n-tuple size. Apparently

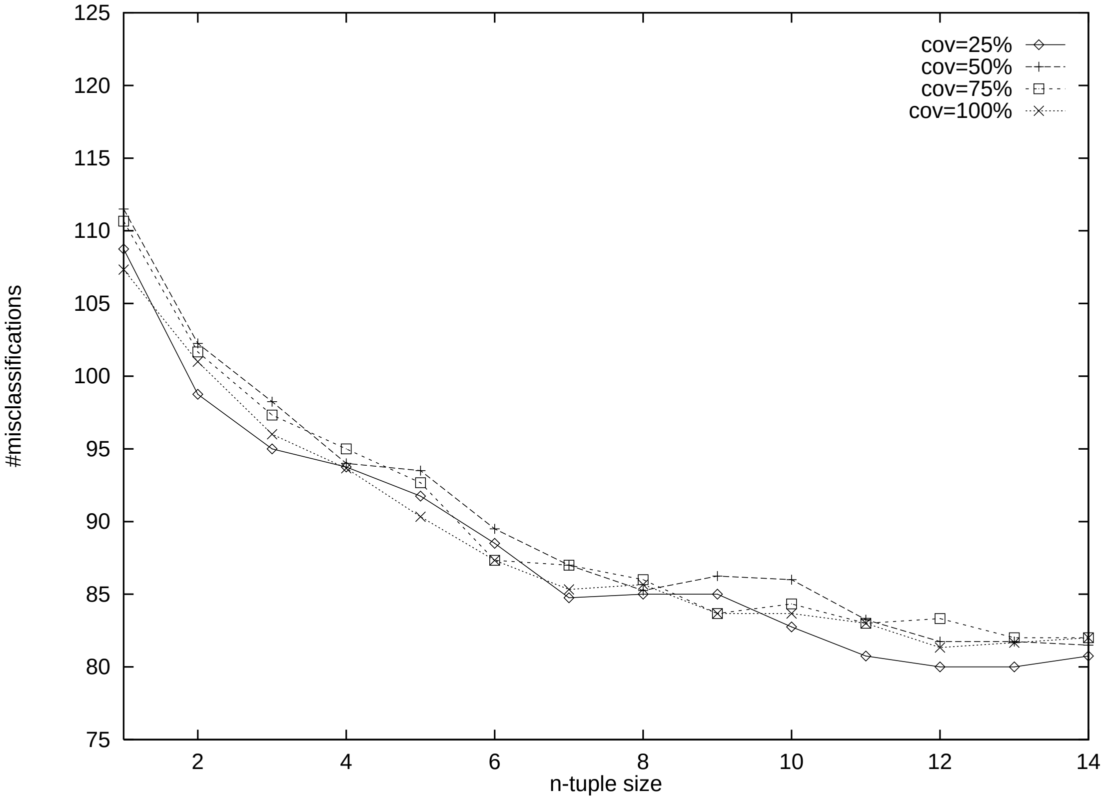

Figure 6.4: Test results with Uniform Random retina

this n-tuple size must bigger than 14 for this data set. There does not seem to be much difference between the different coverage percentages. The number of misclassifications is the number of wrongly classified beats out of the total number of 2437 beats in the testing part of record 208 (see table ??). So the lowest misclassification reached in these experiments, 75 (n-tuple size = 12, `coverage` = 25% and `seed`=4), means a correct classification of $\frac{2437-75}{2437} \times 100\% = 96.9\%$[1].

6.4 Test 2: The Normal Distributed Retina

As discussed in section ?? the uniform random distributed retina does not incorporate prior knowledge about the ECG signal. This section shows the results of experiments similar to those of section ??, except that the retina is taken to be partially normal and partially uniform random distributed, as shown in figure ?? on page ??. The used `dist-ratio` is 0.3, so 70% of the retina points originate from the

[1]This term will be referred to as classification rate.

normal distribution, and the remaining 30% are randomly chosen from the window. The experiment were performed for `coverage` $= 25, 50$, 75 and 100%, and n-tuples ranging from 1 to 14.

The other parameters:

`wsize`	=	300
`wres`	=	200
$\mathtt{T}_{\min}$	=	300
$\mathtt{T}_{\max}$	=	1800
`beatratio`	=	0.5
`dist-ratio`	=	0.3
`cutoff`	=	50

Unless stated otherwise, this is the configuration used throughout the subsequent experiments.

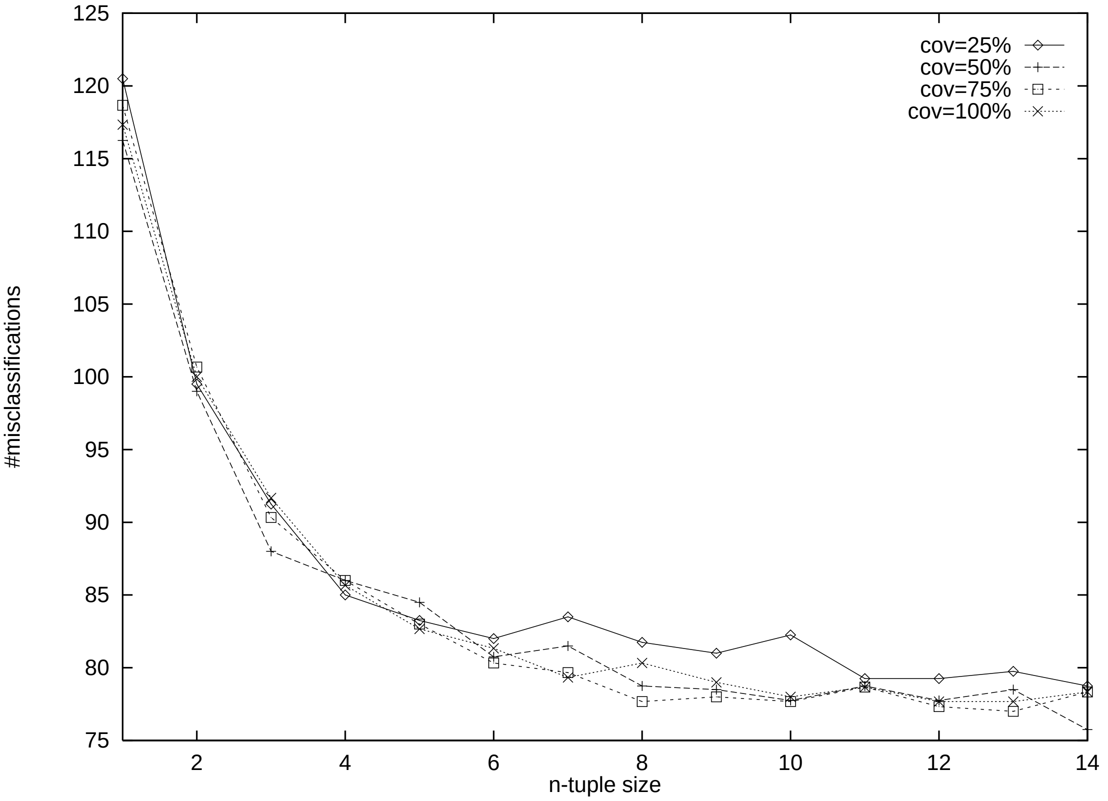

Figure 6.5: Test results with 'Normal' retina (`ratio` $= 0.3$)

The results of this test show the same trend as obtained previously with the uniform random retina: the higher the n-tuple size, the better the classification. On average the results were slightly better (approximately 5 misclassification less) than the corresponding uniform random retina setup, especially for the n-tuple sizes 3 to 7. The highest classification rate was 97.0% for $n = 14$, `coverage` = 50% and `seed` = 1.

In order to get some more insight into the way the results react on changing the parameters (parameter sensitivity) a series of experiment has been performed for `coverage` ranging from 10 to 100% (step-size 10%) and n-tuple = 1 to 16.

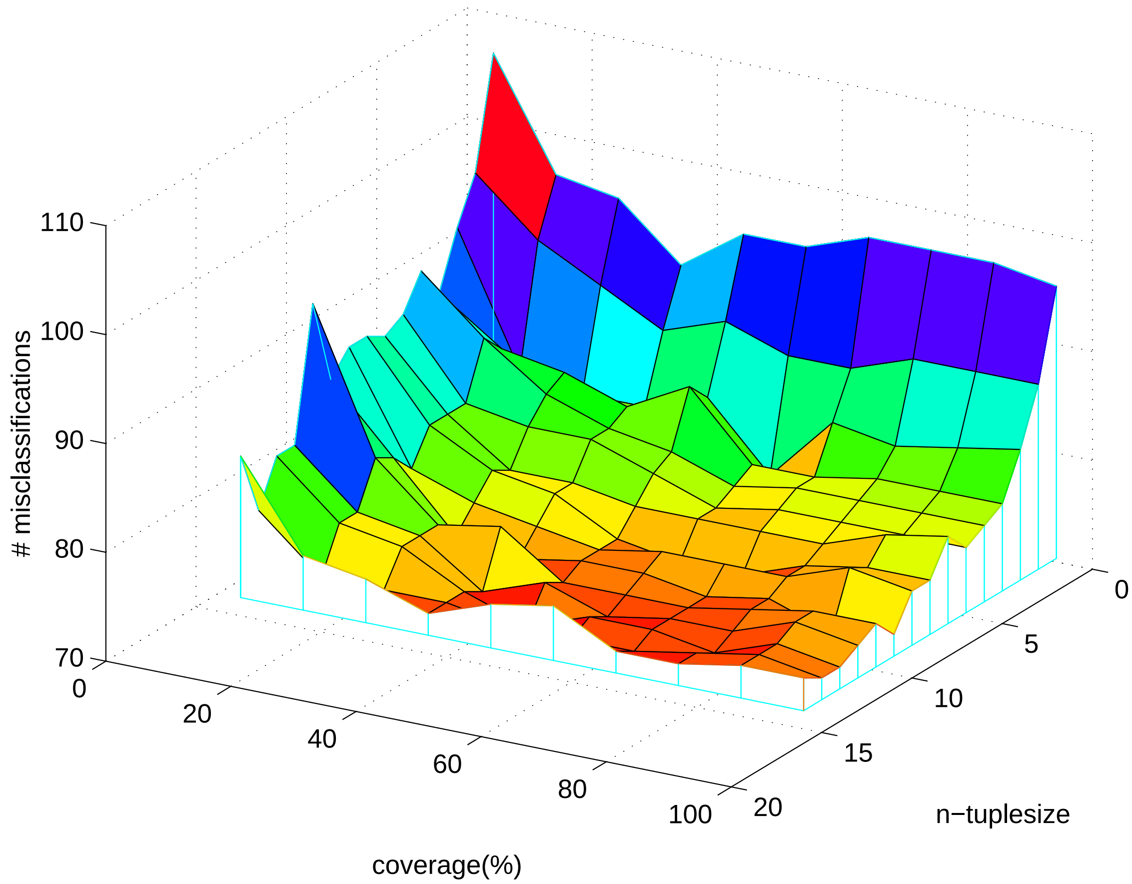

Figure 6.6: Test results for n=2-16, `coverage`=10-100%

Figure **??** shows that the results for `coverage` = 40 - 100 % and n-tuple size 9 - 16 are approximately the same: apparently the system is quite insensitive for parameter choosing within certain limits.

The results for $n = 1$ are left out of this figure: as table **??** shows the numbers of misclassifications were so high that they distorted the figure. These results are presented in table **??**.

`coverage`	misclassifications
10 %	149
20 %	125
30 %	122
40 %	120
50 %	119
60 %	116
70 %	121
80 %	120
90 %	117
100 %	116

Table 6.1: Results for $\mathtt{n} = 1$

6.5 The Confidence Interval

Figure **??** illustrates the average confidences for the experiments performed in the last section. This is, for all the (in)correct classifications of a certain n-tuple size and `coverage` the confidence is averaged. The upper plane is the average confidence of the correct classifications and the lower the average confidence of the misclassifications.

The confidence is the relative difference between the highest and the second highest output of the discriminators. This is equivalent with the relative difference of the number of RAM-nodes with output 1 of the two discriminators. Figure **??** shows that the both the confidence measures increase if the n-tuple size increases, and that the `coverage` has hardly any influence. The relation between the misclassification-confidence and the correct classification confidence seems to be linear: the former is approximately half the latter. This makes the confidence an unsuitable measure for selecting the parameter values. This observation was not only made for these experiments: all experiments performed displayed the same trend.

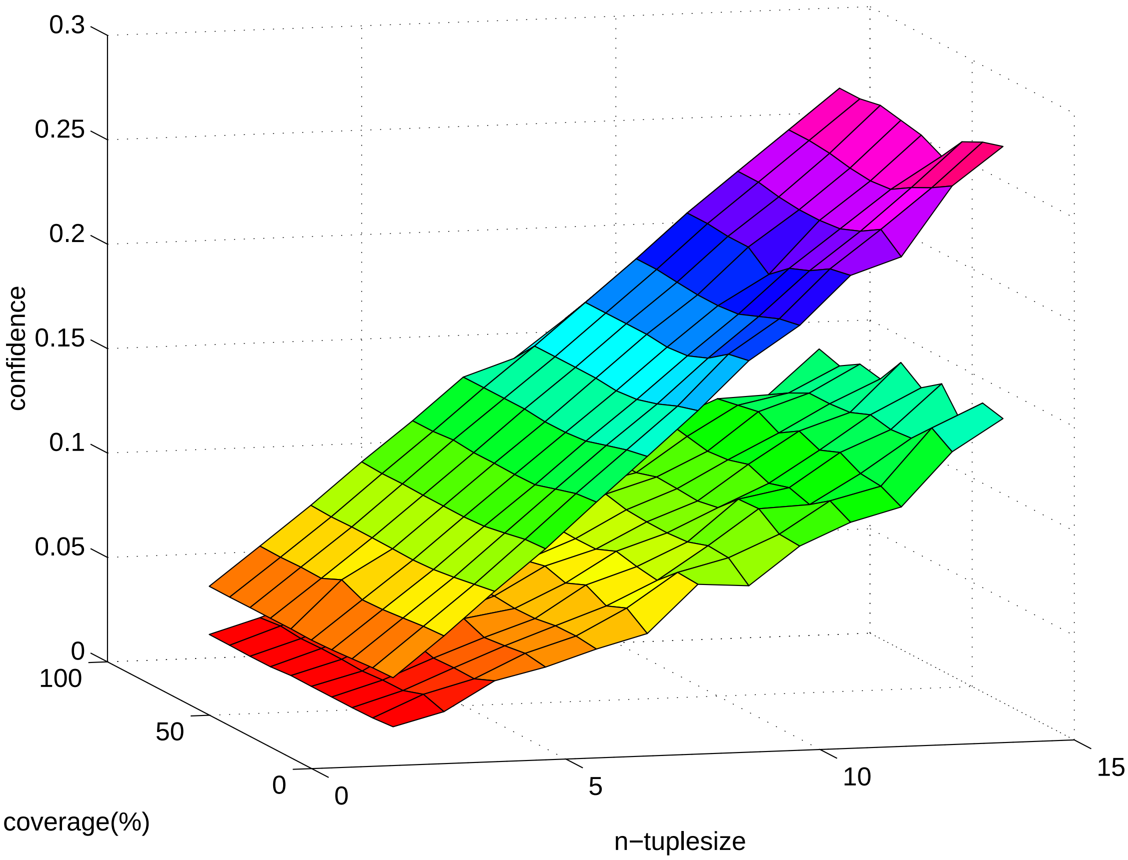

Figure 6.7: Confidence planes for correct and incorrect classifications

6.6 Test 3: `dist-ratio`

The following set of experiments were performed to investigate the influence of the ratio of uniform random distributed retina points and normal distributed retina points, the `dist-ratio`. The experiments were performed for $n = 9$, and for `coverage` = 25, 50, 75 and 100%. The `dist-ratio` changed from 0 to 1 (step size = 0.1).

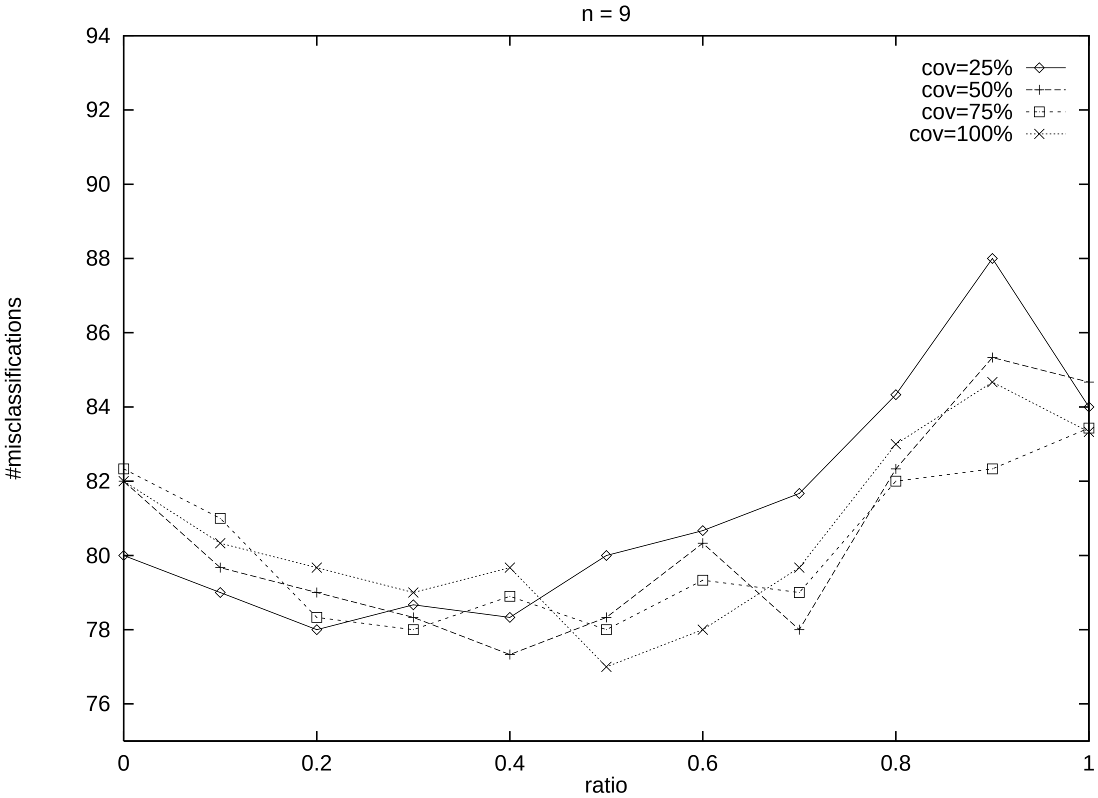

Figure 6.8: Test results for `ratio`= 0 - 1, n = 9

The best value for `dist-ratio` lies some where between 0.2 an 0.7. Again there is not much difference which value is chosen for `dist-ratio`, as long as it lies within these limits.

6.7 Test 4: The Length of the Training Period

In order to investigate how well the system was trained, the length of the training set can be varied. In the following experiments the system was trained for a $\mathtt{t_{train}}$

= 60, 120, 180, 300, 420 and 600 seconds[2]. The test period was reduced from 25 to 20 minutes, because the total length of the record is only 30 minutes. Table **??** show the number of beats in each training set and for the test set.

	t=60	t=120	t=180	t=300	t=420	t=600	test-period
N	64	117	164	279	410	510	1075
V	31	67	105	168	223	367	626
F	11	23	38	71	93	136	236
total	106	207	307	518	726	1013	1937

Table 6.2: Number of beats in the training periods

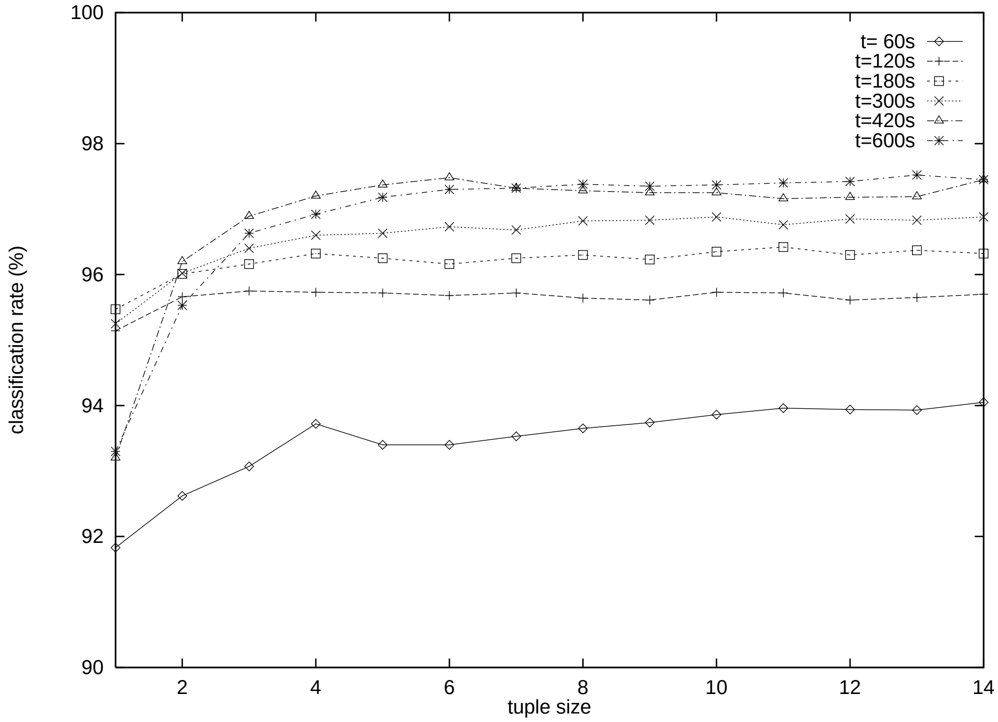

Figure 6.9: Test results for different training times

Figure **??** shows classification rate plotted against the n-tuple size. `coverage` is 50%, and the normal distributed retina was used with a `dist-ratio` of 0.3.

[2]for convenience referred to as t = 1 (minutes), t = 3 etc..

As expected a longer training period gives better results than shorter ones, up to a certain point. The results of a training period of 600 seconds are better than for a training period of 420 seconds, but the difference is only marginal. The standard of 5 minutes training seems good period for this approach.

For n-tuple sizes of 1 and 2 this is slightly different. In figure **??** the test results for $n = 1$ and 2 and training times ranging from 60 to 600 seconds are plotted. As can be seen the results for training periods longer than 360 seconds for $n = 1$ and longer than 420 seconds for $n = 2$, are worse than they are for shorter training periods. This is due to saturation of the memory: the memory of the RAM nodes get filled with ones, for one or more discriminators, and the saturated discriminator(s) generate high outputs on every input they get. This often results in a lower classification rate.

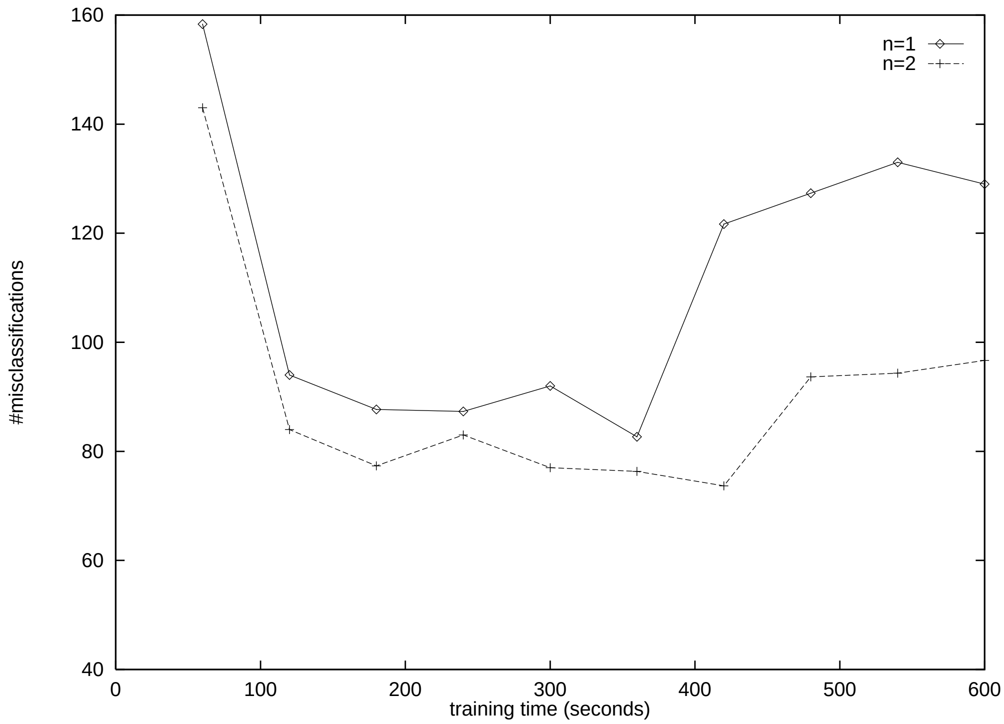

Figure 6.10: Test results for $\mathtt{n} = 1$ and $\mathtt{n} = 2$

6.8 Test 5: Window Size

The `wsize` determines how much of the record the system uses as input. A `wsize` = 300 corresponds with approximate one beat at a heart rate of 72. The system is tested with `wsize`s of 350, 300, 250 200 and 150, n-tuple sizes varying from 1 to 14 and the `coverage` of the normal distributed retina = 50 %.

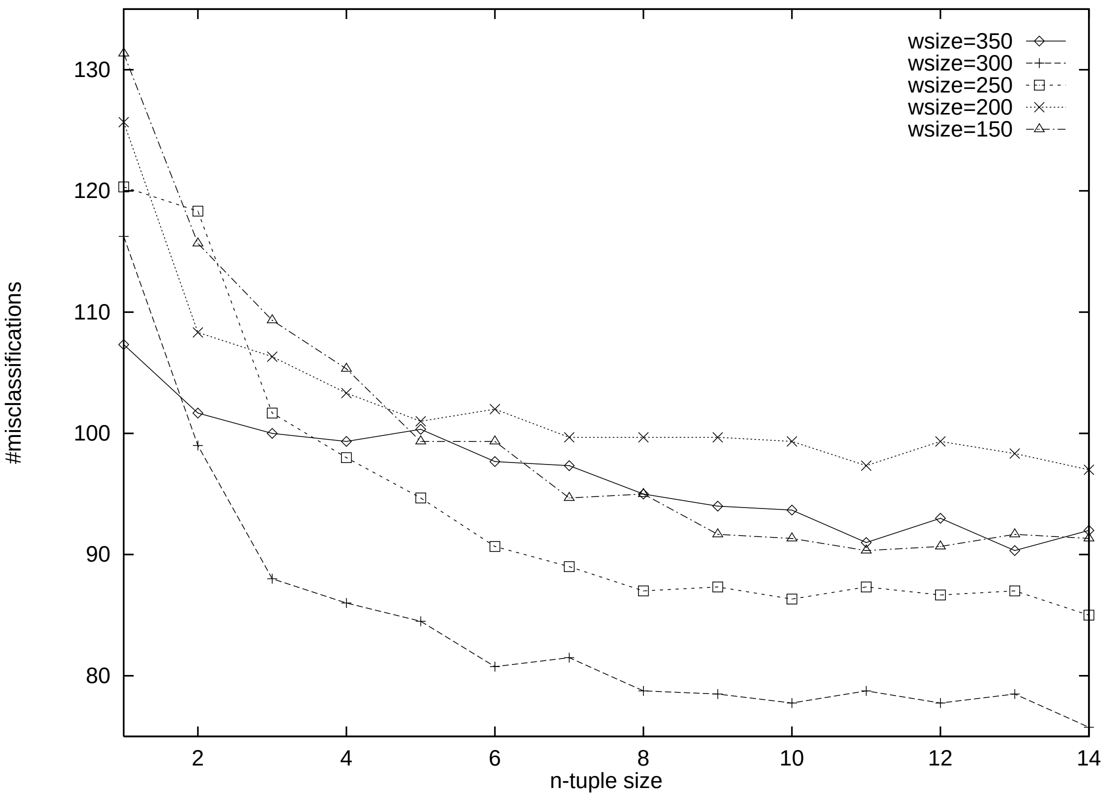

Figure 6.11: Test results for `wsize`

Figure ?? shows that `wsize` = 300 is a good choice. The number of misclassifications is significantly lower than for the other values. The reason why increasing `wsize` from 300 to 350 do not give an improvement is that the edges of the window get filled with parts from preceding or following beats, for which the class may vary. So sides of the windows can be considered noisy, and the results worsen accordingly. For smaller `wsize` the results are worse because the loss of all information about the preceding and following beat.

6.9 Test 6: Training with Threshold value

In order to prevent the memories of the RAM-nodes from becoming saturated with ones, Tarling and Rohwer [?] suggest a 'testing before training' algorithm.. Saturation is the problem that the contents of the memory locations tend to go to 'solid' ones because the locations in the memory are set but never reset. This causes the loss of the generalisation capacity of the network. If the test pattern is classified correctly, the pattern is skipped, and else the discriminator for the class of the patterns is trained with the pattern.

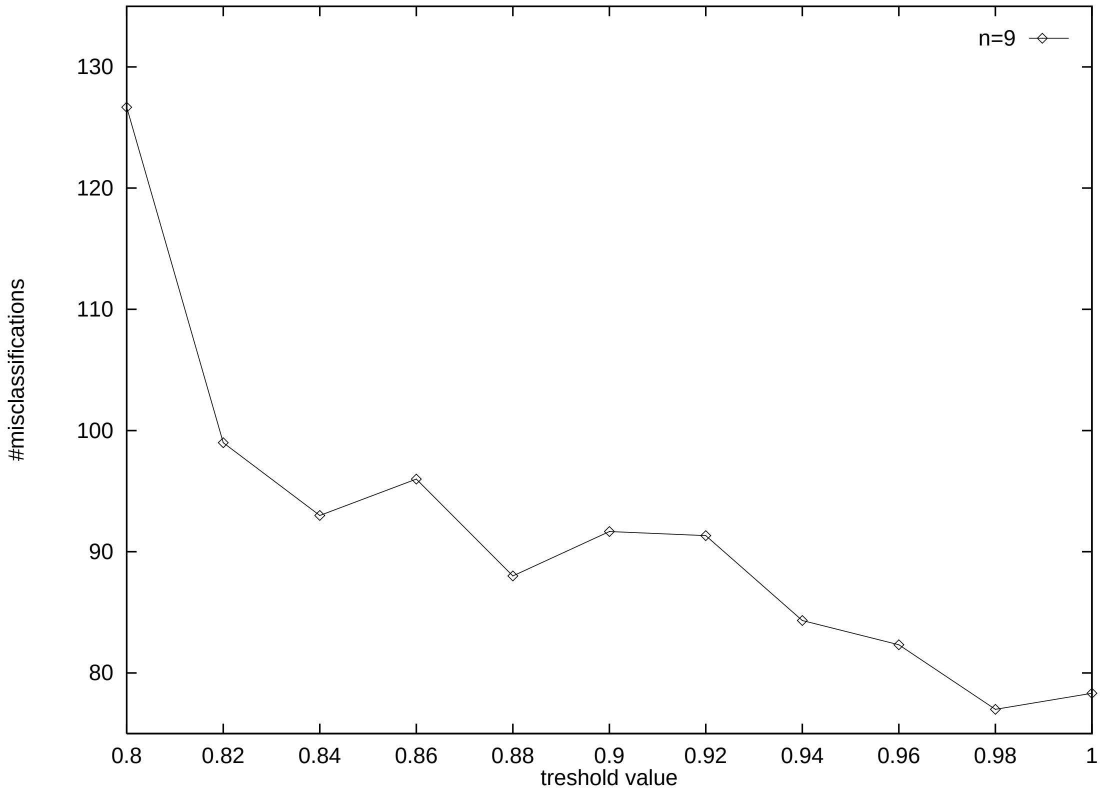

Figure 6.12: Test results for Training with a Threshold

This algorithm was tested, but with very poor results: most of the beats were skipped, and the results of the systems trained on only a few beats were very poor. The results of the experiments presented here are the results of experiments performed with a modified version of this algorithm. The candidate training pattern is also tested before training, and if the outcome of the appropriate discriminator is lower than a certain `threshold` value, the pattern is used for training, otherwise it

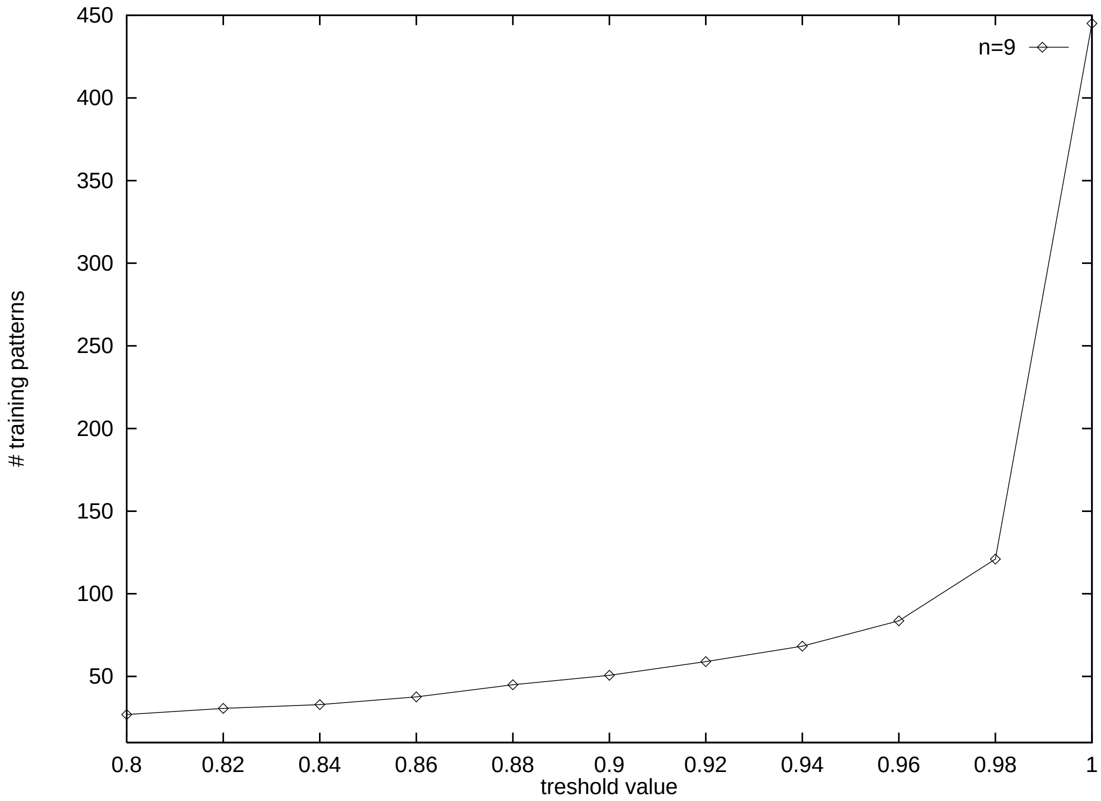

Figure 6.13: Number of Patterns used while Training with Threshold

is skipped.

Figure ?? shows the results of the experiments performed using training with a threshold. The threshold value is ranging from 0.8 to 1.0 and $n = 9$. A normal distributed retina was used with `dist-ratio` $= 0.3$.

The number of beats trained for each value of `threshold` is shown in figure ??. One can see that using a `threshold` of 0.98 reduces the number of trained samples by a factor 4.5 (without threshold 517 beats are used for training, see table ??), and that the results are about the same as for training without threshold.

From the result for `threshold` $= 1$ (figure ??) we can deduce that about 70 patterns in the training set are superfluous; the response of the discriminator for these patterns is 1, which means that all the memory location addressed by the pattern were already set, and the beat was skipped.

6.10 Other Records

This section shows some results for some other records than record 208. The results mentioned are the best results seen, but the testing on these record was far from thorough.

rec.	n-tuple	*coverage*	*classes*	*class%*	*remark*
102	6	50%	4: NVPf	99.2%	unbalanced training set
104	8	50%	4: NVPf	97.3%	unbalanced data sets
105	12	50%[1]	2: NV	99.5%	only few V beats
106	8	50%	2: NV	99.7%	[2]
107	9	100%	2: VP	97.7%	unbalanced data sets
119	9	50%	2: NV	99.8%	
208	14	50%	3: NVF	97.0%	

Table 6.3: Results for other records

[1] an uniform random retina was used
[2] a test before training threshold of 0.95 was used: 288 out of 330 beats were skipped

6.11 A Comparison

6.11.1 Weightless Results

In section **??** the classification rate of 97.0 % was mentioned. This result was obtained for a 'normal' retina, $n = 14$, `coverage` $= 50$ % and `seed` $= 1$. The number of misclassification was 73 out of 2437 beats. Table **??** shows the classifications of that experiment, the sensitivity and specificity. The entries represent the number of beats from the row header class which are classified by the system as belonging to the class of the column header.

Sensitivity is the percentage of correct classified patterns from a class out of the total number of patterns in that class. *Specificity* is the percentage of correct classified patterns from a class out of the total number of beats classified as belonging to that class.

The results as shown in table **??** are encouraging. Especially the high sensitivity en specificity percentages for the class of the normal beats is important: this means

	N	V	F
N	1303	0	4
V	5	791	28
F	15	16	270
Q	3	1	1
Sens.	99.69	96.00	89.70
Spec.	98.27	97.90	89.11

Table 6.4: Results for Weightless Network

that almost all of the normal beats are classified as normal, and that from the beats classified as normal only a small percentage abnormal is. The number of incorrect classifications V beats in the Fusion-class (28) and vice versa (16) show that there is some overlap between these classes. Surprisingly this overlap doesn't appear in the Sammon mappings as shown in chapter **??**.

The classification of F beats is the most problematical. Only 89.70 % of the F-beats are classified correct. This supposedly has to do with the fact that the F-discriminator was trained with the lowest number of training patters (71, against 168 for the V-discriminator and 279 for the N discriminator).

6.11.2 Other Results

Table **??**, **??** and **??** show classification results for record 208. These results are mentioned in [**?**]— a publication about similar work by Ramirez-Rodriguez and Vladimirova.

Table **??** lists the results of a Hybrid Neuro-Fuzzy System (HNFS) for the classification of ECG beats. This system is developed by Ramirez-Rodriguez and Vladimirova at the University of Surrey. Their HNFS has a hierarchical topology consisting of three kinds of building blocks — fuzzy neural networks, neural networks and fuzzy systems. The (fuzzy) neural networks are based on the feedforward backpropagation model. The systems uses the 2 ECG leads as input for two fuzzy neural networks, and a inference system is used to support when the classifications of these two neural nets differ. The best classification rate of this system is 97.74 % with 55 misclassifications out of 2437 patterns.

The results in table **??** were obtained from a feedforward multilayer perceptron (MLP) with a backpropagation training algorithm, build for comparison proposes. Both of the signals were used as inputs, and the same decision mechanism was used as for the HNFS. For this system the best classification rate was 95.53 % (109 misclassifications).

	N	V	F
N	1294	0	16
V	4	795	23
F	5	2	293
Q	0	0	2
Sens.	98.78	96.48	97.34
Spec.	99.31	99.75	87.72

Table 6.5: Results for HFNS

	N	V	F
N	1295	1	14
V	23	792	7
F	54	5	241
Q	1	0	1
Sens.	98.85	96.12	80.07
Spec.	94.32	99.25	91.63

Table 6.6: Results for the MLP

Nadal and Bossan developed a ECG classification system based on a Principal Component Analysis (MCA) approach. Results are shown in table **??**. This system obtained with 44 misclassifications out of 2947 patterns, the highest classification accuracy (98.5 %). However, for this system the whole record was used to train the classifier, and the results were obtained by testing the same beats.

	N	V	F
N	1571	4	15
V	0	979	4
F	13	8	353
Sens.	98.80	99.59	94.39
Spec.	99.17	98.78	94.89

Table 6.7: Results for the PCA system

6.11.3 The Comparison

When the systems mentioned earlier are compared according their classification rates, the weightless approach only scores a third place: it only outperforms the multilayer perceptron network. But that comparison is not really a fair one: both the hybrid neurofuzzy system and the multilayer perceptron network use two ECG leads, while the weightless system uses only one. And the principal component analysis based system was trained and tested on the same dataset.

When we look at the systems as novelty detectors (which means classification as normal or abnormal) the weightless neural network is a good alternative for the other networks. The sensitivity and specificity for the class of the normal beats good (first respectively third place), which means that a fairly accurate normal-abnormal classification can be made. On the other hand, the systems were not designed as novelty detectors.

The classification of a record is very fast for the weightless approach: training and testing of a 30 minutes record takes approximately 2 minutes, depending on the parameters. Unfortunately timing data is not available for the other methods. Real time data processing can be easily achieved using weightless neural networks.

Chapter 7

System Evaluation

This chapter contains an evaluation of the weightless neural network used for ECG classification. During the training period several features of the network can be measured, like the number of ones in the memories of the RAM nodes and the output of the discriminator just before training a pattern.

7.1 The Filling of the Memory

During the training phase the memories of the RAM-nodes are filled with ones. The growth if the number of ones in the memory locations of the RAM-nodes of a certain discriminator should converge to a certain number. When this number is reached new patterns fed into the network are already recognised by the discriminator and it produces a high output.
The experiments was performed with the following parameter values:

$$\begin{aligned} n\text{-tuple} &= 10 \\ \texttt{coverage} &= 50\ \% \\ \texttt{T}_{\text{min}} &= 300 \\ \texttt{T}_{\text{min}} &= 1800 \\ \texttt{dis-ratio} &= 0.3 \end{aligned}$$

This means there are $3000 \times 2^{10} = 3,072,00$ memory locations which can be set to one for each discriminator.

Figure **??** illustrates the number of ones in the discriminators during the training of pattern 208. Not that the x-axis values are the number of patterns trained for

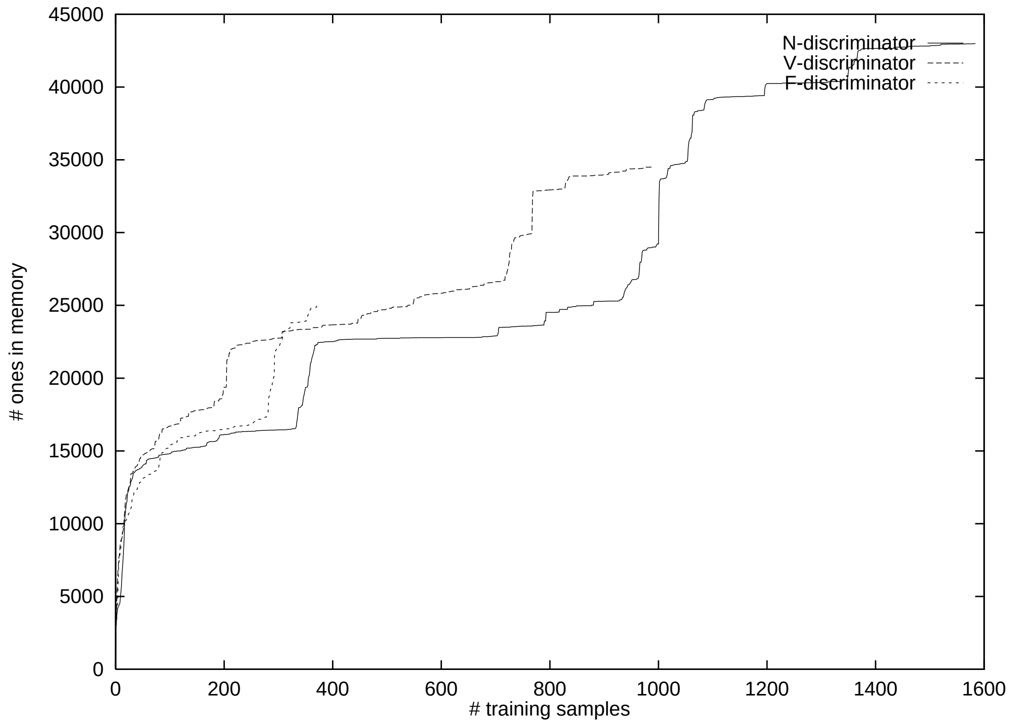

Figure 7.1: Number of '1's during training

that particular class. For the training the whole record was used.

The graphs in figure **??** show a large growth in the beginning of the training: the first training pattern causes a growth of 3000 (in each RAM-node one location will be set to one). After this the graphs flatten out. The plot for discriminator F shows one abrupt increase (after approximately 300 training patterns), where as the plots for the other two discriminators show two abrupt changes. These changes are caused by noisy periods in the data as will be discussed later.

These noisy periods have not been of much influence of the experiments described in the previous chapter: the noisy periods appear after the first five minutes of the data.

7.2 The Generalisation

In order to investigate how well the network is trained, one might look at the performance of the discriminators just before training. When the discriminators are trained on the whole pattern, this gives the results shown in figures **??**, **??** and **??**.

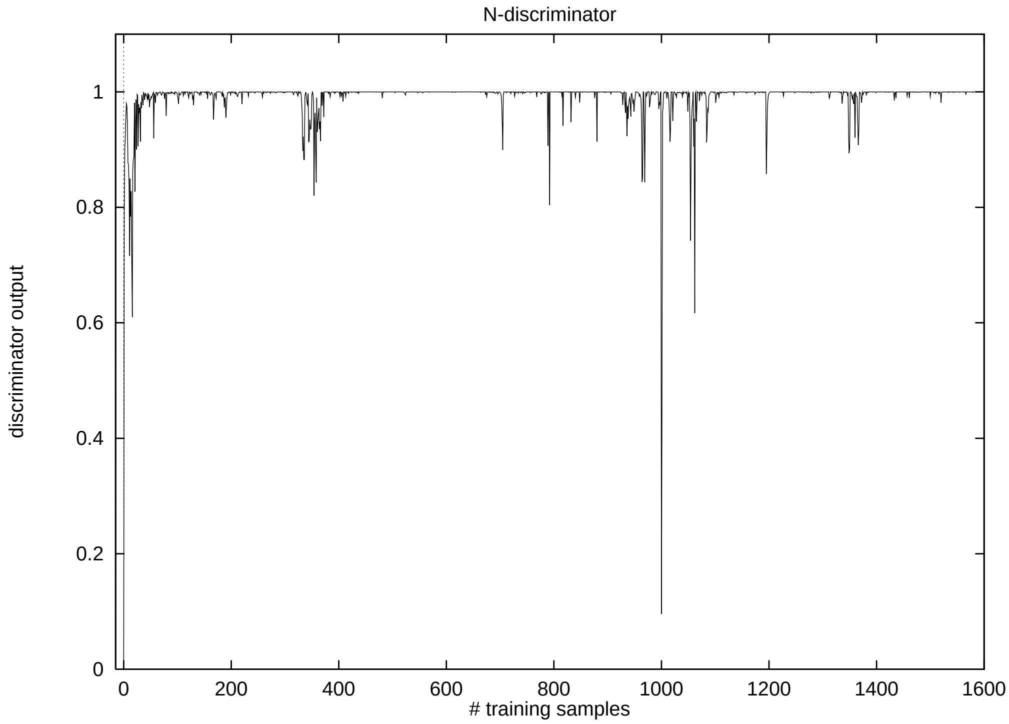

Figure 7.2: Discriminator N Output during training

All three figures show that the discriminators are trained quite well: for most of the training sample the output of the discriminators is one or almost one. In the figures the noisy periods can be recognised easily: the output of the discriminators.

Visual inspection of the data showed that there are several noisy periods in the signal. The first noisy period appears approximately 6 minutes after the start of the signal. In this noisy period almost no Fusion beats are present, so the noisy does not appear in figure **??**. This period corresponds with the downward peak at approximately the 380^{th} Normal beats in figure **??** and approximately the 200^{th} PVC beat in figure **??**.

A second, and longer, noisy period begins 19.5 minutes after the start of the record and lasts for approximately 25 seconds. This is the period that corresponds to the downwards peaks at ± 1000 patterns in figure **??**, ± 750 in figure **??** and $\pm$ 280 in figure **??**.

This shows also the relation ship between the figures in this section and figure **??** in the previous section: a low output of the discriminator before learning a pattern causes a steep rise of the number of ones in the memory of the RAM-nodes.

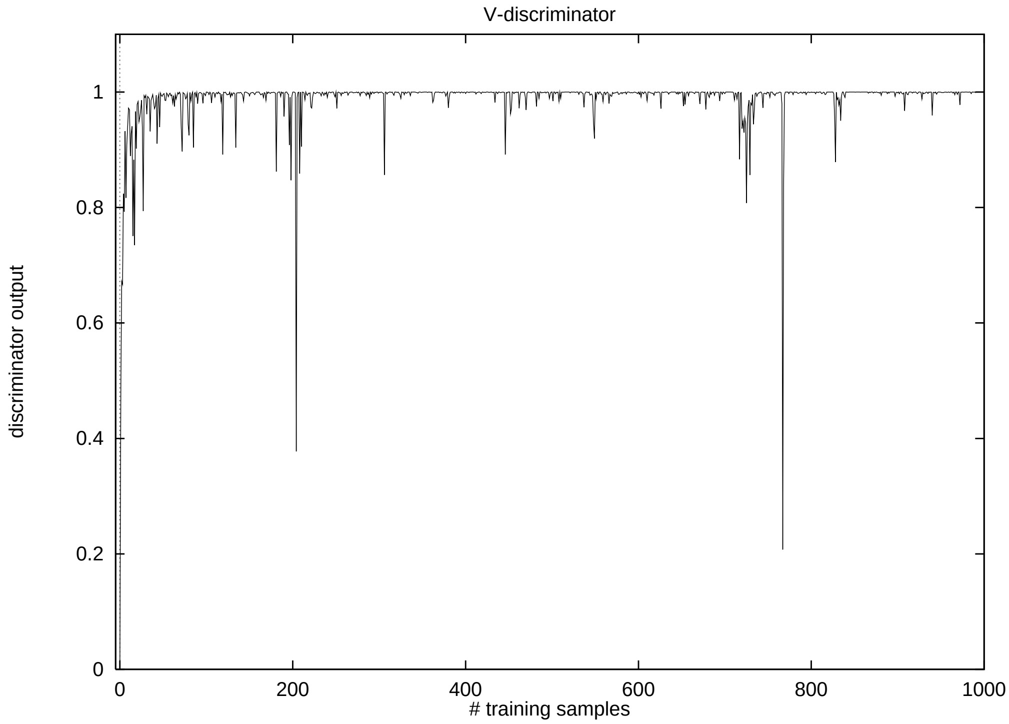

Figure 7.3: Discriminator V Output during training

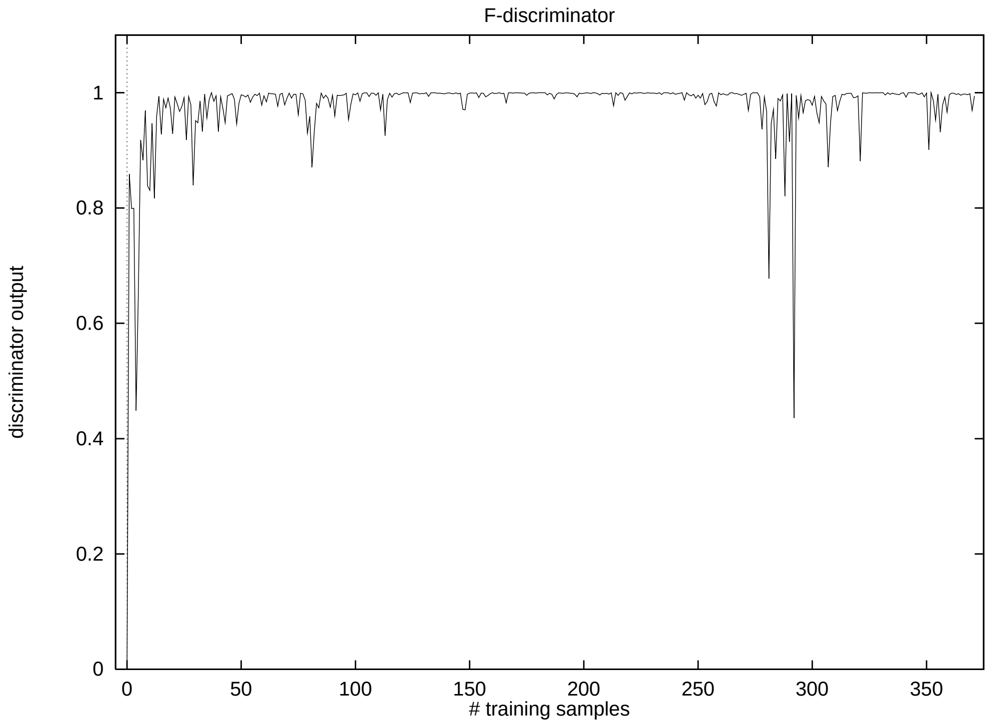

Figure 7.4: Discriminator F Output during training

Chapter 8

Conclusions

8.1 Conclusions

This project has been performed to evaluate the capability of Weightless Neural Networks to perform automated ECG analysis. The primary objective, to classify heart beats extracted from ECG signals into several classes, has been successfully met. A single lead ECG diagnosing system based on the WISARD architecture, reached a correct classification rate of 97.0% for record 208 of the MIT-BIH database.

Although this is not the highest classification rate compared to results seen in other research, the results are still very promising. The results from the other research projects were based on a double lead ECG analysing system, while the system under study here only used a single ECG lead as its input, deprived of the extra information that a two-lead system would convey.

The system turned out to be parameter insensitive, especially for the n-tuple size and the coverage percentage of the retina. When these parameters vary within a certain region, the results stay approximately the same. The relative confidence of the classifications is also not a measurement on which a best parameter setup can be decided; the confidence of the correct classification is in general approximately twice as big as the confidence of the incorrect classification.

Overall one can say that the weightless neural network is competitive with other neural network methodologies. Its simplicity makes it easy to implement, train and use. Its speed can be seen as an advantage over other methods. Real time ECG processing can be easily achieved using weightless neural networks.

8.2 Recommendations

The results of the system can probably be improved by using both leads of the ECG as inputs for the system. The two leads can be combined as the input for one neural network, but it is probably better to train two weightless neural networks, one for each lead. Tie-breaking in conflicting outputs of the networks can be achieved by using an Expert System, or training a third (weightless) neural network on the output of the other two (for example, the classes and confidences).

The only preprocessing used in this research is the thermometer coding of the data. It might be worthwhile to investigate the results obtained with other coding methods, most of which involve much more preprocessing. It is also interesting to see whether the results based upon a feature-vector approach give an improvement. Features that can be used in the feature vector can be QRS hight and width, ST-segment placing, inter QRS distances etc. Although these are interesting questions, it might not be the best possible preprocessing method in combination with weightless neural networks. The power of the method used in this research lies in the simplicity of the algorithm, and letting the neural network do the difficult job of choosing the features upon which a decision is made.

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Appendix A

Medical Glossary

arrhythmia deviation of the normal rhythm of the heart

artery any of the muscular-walled tubes forming part of the blood circulation system of the body, usually carrying oxygen enriched blood from the heart

coronary blood vessels the arteries which supply the heart with blood which encircle the heart like a crown

coronary thrombosis a blockage of the blood flow causes by a blood clot in a coronary artery.

digitalis drugs prepared from the dried leaves from foxgloves and containing substances that stimulate the heart muscle.

ectopic in an abnormal place or position

endocardium the lining membrane of the heart

endothelium a layer of cells lining in the blood vessels, heart and lymphatics vessels

epicardium the fatty layer on the outer surface of the myocardium

fibrillate (of a ,muscle, esp. in the heart) undergo a quivering movement due to uncoordinated contraction of the individual fibrills

flutter an abnormal rapid, but regular heartbeat

ischemia a reduction of blood supply to part of the body

myocardial infarction a localised area of dead heart tissue caused by inadequate blood supply by the coronary arteries. Also referred to as a *heart attack*.

myocardium the muscular tissue of the heart

pericardium the membranous sac enclosing the heart

precordial in front of the heart

tachycardia an abnormal rapid heart rate

ventricle hollow part of an organ, esp. in the brain or heart

Appendix B

Symbols used in ECG plots

Symbol	*Meaning*
•	Normal beat
L	Left bundle branch block beat
R	Right bundle branch block beat
A	Atrial premature beat
a	Aberrated atrial premature beat
J	Nodal (junctional) premature beat
S	Supraventricular premature beat
V	Premature ventricular contraction
F	Fusion of ventricular and normal beat
[	Start of ventricular flutter/fibrillation
]	End of ventricular flutter/fibrillation
e	Atrial escape beat
j	Nodal (junction) escape beat
E	Ventricular escape beat
P	Paced beat
f	Fusion of paced and normal beat
p	Non-conducted P-wave (blocked APB)
Q	Unclassifiable beat
|	Isolated QRS-like artifact

Table B.1: Symbols used in ECG plots

Appendix C

ECG Rhythms

This section is a list of possible observations that can occur in ECG signals . The list is meant as a reminder to health care professionals. Some of the observations are benign, as others require immediate medical action. The source of this list is world-wide-web site of the University of Oklahoma Health Sciences Centre (*http://einthoven.uokhsc.edu*), which is maintained by David. A. Thong and Lawrence E. Widman.

Normal Sinus Rhythm This is a normal rhythm, and is not of diagnostic significance unless the rate, which ranges from 60 to 100 beats per minute, is not appropriate for the clinical setting.

Sinus Tachycardia This rhythm differs from normal sinus rhythm only in that the rate is above 100 beats per minute. The differential diagnosis is extensive. Common causes are anxiety; physiological stress such as hemorrhage, dehydration, sepsis, and fever; and hyperthyroidism.

Sinus Bradycardia This rhythm differs from normal sinus rhythm only in that the rate is below 60 beats per minute (bpm). This can be a normal finding in young patients, particularly in athletes. It can be caused by medications, including as beta blockers, some calcium blockers such as diltiazem, aldomet, and perhaps digitalis.

Hidden Atrial Activation Activation of the atrium by the sinus node can be inferred from surrounding sinus P waves. For example, if the P wave following a ventricular premature complex occurs at the time that would have been expected had the premature complex not occurred, then in can be inferred that the atrium was not activated retrogradely by the premature complex and that a hidden, or obscured, P wave did occur.

Sinus Arrhythmia This rhythm is usually a benign finding. It is characterised by variations in the heart rate from cycle to cycle that are greater than would be expected from normal respiratory variation. When pronounced, it can be symptomatic.

Sinus Arrest This rhythm results from failure of the sinus node to activate the atria. When it is of short duration (less than one to two seconds), it is usually benign. When it is of long duration (greater than or equal to three seconds), it can be life-threatening because of the potential for longer periods of sinus arrest with asystole. It can be caused by medications, including as beta blockers, some calcium blockers such as diltiazem, aldomet, and perhaps digitalis. It can also be part of the sick sinus ('tachy-brady') syndrome, which is one of the leading indications for implantation of permanent pacemakers.

Atrial Premature Complex This is a P wave that occurs earlier than would be expected from the sinus rate, and that usually has an abnormal morphology. It can fail to conduct through the atrioventricular node, in which case it will not result in a QRS complex. When it does conduct through the atrioventricular node, it can be conducted aberrantly if it traverses the bundle branches of the His-Purkinje system while one or both is in its relatively refractory period. Aberrantly conducted QRS complexes are wider than normal, and have the morphology of bundle branch block pattern.

Atrial premature complexes are a normal finding in adults of all ages. The frequency can be increased during stress, with ingestion of caffeine, and with sympathomimetic drugs such as some over-the-counter cold remedies.

Atrial Couplet This is a pair of atrial premature complexes in a row. While it is less common in normal subjects than are atrial premature complexes, it can still be benign. The appearance of atrial couplets should also raise the index of suspicion for susceptibility to atrial fibrillation, atrial flutter, and supraventricular tachycardia.

Atrial Multiform Couplet This is a pair of atrial premature complexes, with differing P wave morphologies, in a row.

This is unusual in normal subjects, but is itself benign. The appearance of multiform atrial couplets, especially in patients with pulmonary disease, should raise the index of suspicion for susceptibility to multifocal atrial tachycardia, atrial fibrillation, and atrial flutter.

Atrial Escape Complex This is a P wave that occurs later than would be expected from the sinus rate. Like all escape complexes, it can occur only when the normal cardiac pacemaker does not function, as is *sinus arrest.*

Atrial Tachycardia This is a supraventricular rhythm resulting from either an atrial automatic focus or a reentrant circuit that lies entirely within the atrium. It is characterised by a rate more than 100 beats per minute, and a P wave morphology that is usually different from that of the sinus P wave. It can be intermittent or incessant (present more than 50% of the time). When it is incessant, it can cause symptomatic dilated cardiomyopathy that is reversible with control of the tachycardia.

This is an abnormal rhythm that can result from *digitalis toxicity*, particularly when it occurs in combination with Atrioventricular Nodal Block, Mobitz Type I (Wenckebach).

Atrial Flutter This is a supraventricular rhythm resulting from a reentrant circuit that lies within the right atrium. It is characterised by an atrial rate of 250 to 350 beats per minute, and a ventricular response that is usually about 75, 150, or 300 beats per minute. Flutter waves are best found in ECG leads II, III, V_F, and V_l. Sometimes they are located at the onset or offset of the QRS complex, and are best found by comparison with the QRS morphology in a 12-lead ECG recording obtained during sinus rhythm. Even if flutter waves are not found, this rhythm should be suspected when the ventricular rate ranges from 140 to 160 beats per minute and there is no clear evidence of atrial activity.

It can occur alone, but is usually associated with hypertensive cardiomyopathy, COPD, or congestive cardiomyopathy. The new onset of either rhythm is seen in about 5% of cases of acute myocardial infarction.

Atrial Fibrillation This is a supraventricular rhythm resulting from multiple reentrant circuits within either the right or left atria, or both. It is characterised by an irregularly irregular ventricular rate that is usually rapid in young patients, but may be normal or even bradycardic in elderly patients or patients taking medications that can cause atrioventricular nodal blockade.

It can occur alone, but is usually associated with hypertensive cardiomyopathy, COPD, or congestive cardiomyopathy. The new onset of either rhythm is seen in about 5% of cases of acute myocardial infarction.

In the presence of an accessory atrioventricular pathway, atrial fibrillation can manifest as a rapid, irregularly irregular wide complex tachycardia that can resemble ventricular tachycardia closely. It should be suspected particularly in young patients with very rapid tachycardia that is well tolerated hemodynamically. Close examination of the ECG will reveal irregularly irregular RR intervals.

Wandering atrial pacemaker This is a supraventricular rhythm resulting from multiple ectopic foci in the atria. It is characterised by three or more P wave morphologies and a rate less than 100 beats per minute. It itself is benign, but reflects electrical abnormalities in one or both atria that increase the likelihood of multifocal atrial tachycardia or other atrial arrhythmias.

Multifocal Atrial Tachycardia This is a supraventricular rhythm resulting from multiple ectopic foci in the atria. It is characterised by three or more P wave morphologies and a rate greater than or equal to 100 beats per minute. It is seen most frequently in patients with severe pulmonary disease. The rapid ventricular rate can be symptomatic (hypotension, angina, congestive heart failure).

Junctional Escape Complex This is a QRS with normal morphology for the patient that is not preceded by a P wave and occurs later than would be expected from the sinus rate. Like all escape complexes, it can occur only when the normal cardiac pacemaker does not function, as is sinus arrest.

Junctional Premature Complex This is a QRS complex that occurs earlier than would be expected from the sinus rate, and that usually has a normal morphology for the patient. It can fail to conduct retrograde through the atrioventricular node, in which case it results in a compensatory pause. That is, the next P wave occurs at the same time as would be expected had the VPC not occurred. More usually, it does conduct through the atrioventricular node, so that the following P wave may occur either sooner or later than would be expected.

Junctional premature complexes are relatively uncommon. They can be seen with increased frequency during stress, with ingestion of caffeine, and with sympathomimetic drugs such as some over-the-counter cold remedies. They can also be misdiagnosed when the P wave of an atrial premature complex is obscured by the preceding T wave.

Junctional Rhythm This is a slow rhythm, with rates ranging from 40 to 60 beats per minute, with QRS complexes that have the patient's normal morphology. Usually, no P waves are seen. When P waves are present, they follow closely after the QRS complexes.

This rhythm results from the backup pacemaker capability of the atrioventricular node during sinus arrest.

Accelerated Junctional Rhythm This is a supraventricular rhythm resulting from a focus in or near the atrioventricular junction. The rate ranges from 60 to 100 beats per minute.

This is an abnormal rhythm that can result from digitalis toxicity, particularly when it occurs in combination with atrial fibrillation. It can also result from physiologic stress and other causes of increased sympathetic nervous system tone.

Junctional Tachycardia junctional tachycardia This is a supraventricular rhythm resulting from a focus in or near the atrioventricular junction. The rate is greater than or equal to 100 beats per minute. See also Accelerated junctional rhythm.

This rhythm usually results from a primary arrhythmia rather than as a response to physiologic stimulation. The electrocardiogram usually cannot distinguish this rhythm from the more common types of Supraventricular tachycardia, for which different treatments may be appropriate.

Atrioventricular Nodal Block This refers to an excessively long PR interval only. All P waves are conducted through the atrioventricular node to the ventricle. By itself, it is a benign condition, but may result from disease in the atrioventricular node, high vagal tone, or medication that reduces conduction through the atrioventricular node.

Atrioventricular Nodal Block, Mobitz Type I (Wenckebach) This refers to a gradual prolongation of the PR interval, with occasional failure to conduct a P wave through the atrioventricular node to the ventricle. By itself, it is a benign condition, but may result from disease in the atrioventricular node, high vagal tone, or medication that reduces conduction through the atrioventricular node. It is commonly seen in atheletic young patients, particularly during sleep.

This is an abnormal rhythm that can result from *digitalis toxicity*, particularly when it occurs in combination with Atrial tachycardia.

It is distinguished from Atrioventricular Nodal Block, Mobitz type II by the fact that the PR interval of the P wave that follows the non-conducted P wave is at least 10 milliseconds shorter than the PR interval of the P wave that precedes the non-conducted P wave. Typically, the QRS complex is unchanged from the patient's normal QRS morphology. By contrast, the PR interval does not change in Mobitz type II block. Mobitz type II block *is dangerous because it can progress to complete heart block and death without warning.*

Atrioventricular Nodal Block, Mobitz Type II This refers to occasional failure to conduct a P wave through the atrioventricular node to the ventricle without a change in the PR interval after the nonconducted P wave compared with before the nonconducted P wave. *This is a dangerous condition because it can progress to complete heart block and death without warning.* Placement of an external pacemaker may be lifesaving if a temporary pacemaker cannot be placed immediately.

This condition, while dangerous, is very unusual. The QRS complex is usually wide, due to extensive disease of the His-Purkinje system, although a narrow QRS complex does not exclude the diagnosis. The clinician should measure the change in PR interval carefully, as described for Atrioventricular Nodal Block, Mobitz Type I.

Atrioventricular Nodal Block (2:1 AV Block) This rhythm is diagnosed when the entire rhythm strip shows only conduction of every other P wave to the ventricle. Because the record does not show two consecutive P waves that conduct to the ventricle, it is not possible to measure prolongation of the PR interval, so that it is *not possible to distinguish between* Atrioventricular Nodal Block, Mobitz type I and the *dangerous* Atrioventricular Nodal Block, Mobitz type II . By convention, recordings obtained at other recent times are used to make this distinction.

(Complete) Heart Block This rhythm is characterised by failure of conduction from the atria through the atrioventricular node to the ventricles. The atrial rhythm is independent of the ventricular rhythm, unless an accessory pathway that conducts antegrade is present. It is most easily distinguished from high-grade atrioventricular nodal block when the atrial and ventricular rhythms are regular but have different rates. Because of weak coupling between the chambers by the autonomic nervous system, these rates can be very close to each other and in fact can oscillate around each other.

Complete heart block is one of three forms of atrioventricular dissociation. The other two forms are:

- sinus arrest or sinus bradycardia with junctional rhythm or Idioventricular rhythm.
- ventricular tachycardia.

Of these three forms, only Complete Heart Block results from antegrade conduction block from the atria to the ventricles.

Ventricular Premature Complex This is a wide QRS complex that occurs earlier than would be expected from the sinus rate, and that almost always has an abnormal morphology. It fails to conduct retrograde through the atrioventricular node in half of patients, in which case it results in a compensatory pause. That is, the next P wave occurs at the same time as would be expected had the VPC not occurred. When it does conduct through the atrioventricular node, the following P wave may occur either sooner or later than would be expected.

Ventricular premature complexes are a normal finding in adults of all ages. The frequency can be increased during stress, with ingestion of caffeine, and with sympathomimetic drugs such as some over-the-counter cold remedies. The frequency is also increased in patients with a tendency to develop ventricular tachycardia.

Ventricular Couplet Two ventricular premature complex es in a row. This can be a normal finding, but is more suggestive of electrical heart disease than are single ventricular premature complexes.

Ventricular Escape Complex This is a QRS that is wide and occurs later than would be expected from the sinus rate. Like all escape complexes, it can occur only when the normal cardiac pacemaker does not function, as is sinus arrest.

Asystole, Ventricular Standstill This is diagnosed when only ventricular escape complexes are present, and they occur very slowly. This is an agonal rhythm that is not consistent with life.

Idioventricular Rhythm This is diagnosed when only ventricular escape complexes are present, and they occur at 20 to 40 beats per minute. This rhythm is barely consistent with life. If you see this, you should consider initiating Cardiopulmonary Resuscitation immediately, and should move the patient to an intensive care unit as soon as possible.

Accelerated Ventricular Rhythm This is diagnosed when only ventricular escape complexes are present, and they occur at 60 to 100 beats per minute. This rhythm is usually seen in the setting of acute myocardial infarction. If the patient is in sinus rhythm, the rate of this rhythm tends to be about the same as the rate of the sinus rhythm. In this case, the two rhythms will speed up and slow down so that they alternately capture the ventricle, with characteristic periods of fusion QRS complexes during the changes in rate .

This rhythm is usually benign. Because it occurs in the setting of acute myocardial infarction, patients who exhibit it are already in an intensive care unit where any malignant sequellae can be treated readily.

Ventricular Tachycardia, General This rhythm is diagnosed when three or more premature ventricular complexes occur in a row at a rate of 100-120 beats per minute or faster. The major clinical distinctions are between *hemodynamically unstable* versus stable ventricular tachycardia and between *sustained* versus unsustained ventricular tachycardia.

Hemodynamically unstable ventricular tachycardia a life threatening emergency for which the ACLS protocol should be initiated immediately. *Synchronized* cardioversion is usually the treatment of choice. Awake patients should be sedated heavily before cardioversion if at all possible.

Sustained ventricular tachycardia defined as having a duration of 30 seconds or more, or being hemodynamically unstable. The immediate treatment is specified by the ACLS protocol. For long-term treatment, it is important to realize that these patients have a 20% to 40% sudden death mortality, when untreated, over the 12 months following initial presentation. Empiric treatment with antiarrhythmic drugs does not reduce this mortality. Effective treatment with drugs and/or an implantable cardioverter defibrillator reduces the sudden death mortality over the next 12 months to 0-2%.

Polymorphic Ventricular Tachycardia This form of ventricular tachycardia is characterised by changing QRS morphology, sometimes accompanied by slight changes in the rate. It is a particularly malignant form of ventricular tachycardia that is thought to be intermediate between ordinary monomorphic ventricular tachycardia, and ventricular fibrillation.

Ventricular Fibrillation This is a lethal rhythm, characterised by absence of both organised electrical and organised mechanical activity. This rhythm is equivalent to cardiac death.

Bundle Branch Block This term refers to the QRS morphology seen when either the right bundle branch or the left bundle branch fails to conduct from the His bundle to the ipsilateral ventricle. Right bundle branch block is characterised by an "M" pattern in V1 and wide S waves in the lateral leads (I, V6). Complete left bundle branch block is characterised by negative forces (QS or rS) in V1 and positive forces (monophasic R wave with no Q wave) in V6. Incomplete left bundle branch block can manifest as left anterior hemiblock or left posterior hemiblock.

Atrioventricular Nodal Reentrant Tachycardia This is a reentrant supraventricular rhythm whose circuit is located in the region of the atrioventricular node. It is characterised by a QRS morphology that is normal for the patient. P waves may or may not be seen, but they follow closely after the QRS if they are seen.

Only about 60% of narrow-complex tachycardias have this mechanism. It is important to note that 20% of narrow-complex tachycardias are atrioventricular reentrant tachycardias , which use a concealed accessory pathway for retrograde conduction.

Atrioventricular Re-entrant Tachycardia (AVRT) This is a reentrant supraventricular rhythm whose circuit includes both the atrium and the ventricle, and that uses an accessory atrioventricular pathway for at least one limb of the circuit. 'Orthodromic' AVRT, which is the most common form, proceeds antegrade (from atrium to ventricle) over the AV node, and retrograde over an accessory pathway. 'Antedromic' AVRT proceeds in the reverse direction, and has is a wide QRS tachycardia except when the accessory pathway is located in the right anteroseptal location very close to the His bundle. When multiple pathways are present, it is also possible for the circuit to use two pathways as a circuit.

P waves may or may not be seen, but they usually do not follow closely after the QRS if they are seen.

Supraventricular Tachycardia This is a generic name for a variety of specific supraventricular rhythms, including Atrioventricular Reentrant Tachycardia , Atrioventricular Nodal Reentrant Tachycardia , and Atrial Tachycardia.

It is also used in reference to any narrow complex rhythm to distinguish it from wide-complex rhythms that could arise in the ventricle. In addition to the specific rhythms mentioned above, this use of the term includes atrial fibrillation , atrial flutter , junctional tachycardia , accelerated junctional rhythm , and multifocal atrial tachycardia.

Parasystole The rhythm that results from intermittent capture of the ventricle by a ventricular focus that has entrance block. That is, it is not depolarised when the remainder of the ventricle is activated. The rhythm is characterised by premature ventricular complexes with variable coupling intervals (intervals from the preceding normal QRS complex to the premature complex) and with constant intervals between the premature complexes. Detection of the latter constancy usually requires finding the least common denominator of the intervals between premature complexes, because of the intermittency of ventricular capture by the focus.

This rhythm is rare. It is usually considered benign, although any premature ventricular activation can induce malignant ventricular rhythms in the ischemic myocardium or in the presence of a suitable myocardial substrate.

Wolff-Parkinson-White Syndrome The term used to describe the presence of one or more accessory atrioventricular pathways that conduct in the antegrade direction, with or without retrograde conduction. Patients with this syndrome are susceptible to atrioventricular reentrant tachycardia and atrial fibrillation.

Reciprocal Complex A QRS complex that is caused by activation of a reentrant circuit rather than by the sinus node. This can be harbinger of atrioventricular nodal tachycardia or atrioventricular tachycardia.

Retrograde Atrial Activation A P wave that occurs because of activation of a portion of the heart below the sinus node, including elsewhere in the atrium, the atrioventricular node (via the fast or a slow AV nodal pathway) or the ventricle (via an accessory pathway). Retrograde P waves typically are inverted in the inferior and right precordial ECG leads (II, III, V_F, and V_l), in which the normal sinus P wave is upright.

Atrioventricular Dissociation This term refers to a group of three categories of rhythms in which the atrial and ventricular rhythms are unrelated to each other. The three categories are:

1. (Complete) Heart Block
2. Sinus Arrest or Sinus Bradycardia with Junctional Rhythm or Idioventricular Rhythm
3. Ventricular Tachycardia

Appendix D

Paper for Computers in Cardiology Conference

This appendix contains a paper submitted to the annual conference of Computers in Cardiology, to be held on September 8 - 11, 1996 in Indianapolis, USA.

The topics presented at the Computers in Cardiology conference are:

- Surface ECG Analysis
- Basic and Clinical Electrophysiology
- Physiological Modelling and Simulation
- Cardiovascular Imaging
- Mechanical Properties of the Cardiovascular System
- Implantable Cardiovascular Devices
- Artificial Intelligence and Medical Informatics
- High Technology and Biomaterials

This paper is submitted for the topics Surface ECG Analysis and Artificial Intelligence and Medical Informatics. The maximum number of pages allowed is 4.